Is There a Glass Ceiling in Sweden?

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1. Introduction

Is there a glass ceiling in Sweden? Using the most recent available micro data (from 1998), we find that the gender log wage gap increases throughout the wage distribution with a sharp acceleration in the upper tail of the distribution. We interpret this as strong evidence of a glass ceiling.

Previous work on the gender gap in Sweden focussed on the average log wage gap between men and women. A micro dataset containing individual wage data was first available in Sweden in 1968. At that time, the average raw wage gap between men and women was estimated to be almost 30%. By 1981, this gap had declined by about ten percentage points, but the gender gap then remained more or less stable through the 1980's to 1991 and then increased slightly towards the end of the 1990's. These developments in the average gender wage gap appear to have been driven by corresponding developments in the overall wage distribution (Edin and Richardsson, 2000). The importance of the overall wage distribution for the magnitude of the average gender wage gap is also illustrated by recent work by Blau and Kahn (1995, 1996) and by Blau (1998). Their analyses suggest that, in the early 1980s, the markedly larger average gender gap in the United States compared to Sweden could be explained by higher overall U.S. wage inequality.

Several attempts have been made to estimate the extent to which the average gender gap is due to differences in human capital attributes such as schooling and work experience versus the extent to which it is due to differences across genders in wages paid for given attributes. Less than half of the gap can be explained by factors such as differences in years of schooling, experience, and tenure (Le Grand 1991, Edin and Richardsson 2000). Further, differences in working conditions do not seem to matter at all for the gender wage gap (Palme and Wright 1992).

All of the above-mentioned work on the gender gap refers to average wage gaps. Although this work is interesting, it is not helpful for addressing the question of whether women encounter a glass ceiling. By a glass ceiling, we mean the phenomenon whereby women do quite well in the labor market up to a point after which there is an effective limit on their prospects. The implication of a glass ceiling is that women's wages fall behind men's more at the top of the wage distribution than at the middle or bottom. To investigate whether a glass ceiling exists obviously requires that the gender gap be examined in different parts of the distribution.

Our findings can be summarized as follows. First, we document the existence of a significant glass ceiling effect in Sweden in the 1990's. That is, the gender log wage gap in Sweden in the 1990's is mainly attributable to the gap at the top of the wage distribution. Second, we examine other wage gaps to see whether this is a general phenomenon. We find that this glass ceiling effect was much less pronounced in the 1981 data and was not at all evident in the 1968 data. Thus, the glass ceiling appears to be a phenomenon of the 1990's in Sweden. We also looked at data from the United States in the late 1990's and did not find a comparable effect. Indeed, the gender wage gap at the top of the Swedish wage distribution is larger than the corresponding gap in the United States despite a much larger average gender gap in the United States. Finally, we looked at the wage gap between recent immigrants and other workers in Sweden. Unlike the gender wage gap, the immigrant wage gap is essentially constant over the entire wage distribution. This suggests that the glass ceiling effect is purely a gender-specific phenomenon. Third, we examine the extent to which the gender gap can be explained by differences between men and women in their labor market characteristics and in their returns to these characteristics. We use quantile regressions to address these questions at various points of the wage distribution. We find that basic labor market characteristics can explain a small fraction of the glass ceiling effect. Differences in returns also explain part of the gap at the top of the distribution, but a substantial unexplained gap still remains.

The remainder of the paper is organized as follows. In the next section, we describe our data sources. Our basic findings are presented in a series of figures in Section 3. Section 4 contains the results of our quantile regressions.

2. Data

In this paper, we use several Swedish datasets. Our primary dataset is the so-called LINDA data. This is a special dataset created by Statistics Sweden (SSW) for research purposes (see Edin and Fredriksson, 2000). LINDA is based on a random sample in 1994 of approximately 300,000 people of all ages.[1] The sample is followed over time as a panel and is complemented each year with new immigrants and newly born individuals to make it a nationally representative dataset in each year. The analysis variables in LINDA are primarily taken from SSW's registers. For 1998, SSW ensured that the employers of the complete LINDA sample reported monthly earnings information. Thanks to this addition to the LINDA data, we have monthly earnings information for all employed persons, except the self-employed.[2]

The major advantage of this data source is its large sample size. The drawback is that only a few explanatory variables are available; most notably, actual work experience is missing. On the other hand, there is good information about educational attainment in these data. Specifically, information on educational level is taken from SSW's register of the educational level of the population.[3]

We also use data from SSW for 1992. These 1992 data are collected from employers in the same manner as the LINDA data. Employers report monthly earnings, working hours, occupation and some additional information for their employees. These data cover all employed persons in the public sector and parts of the private sector.[4] For the part of the private sector that is not completely covered, SSW took a random sample of firms. We take a subsample of the data by applying a subsample weight equal to 0.01 times SSW's sample weight. In so doing, we get a simple random sample of around 29,000 workers.

Finally, we also use data from the 1968, 1981 and 1991 waves of the Swedish Level of Living Surveys (SLLS).[5] In contrast to the SSW data, the SLLS data are collected from interviews with individuals. This data source is the one most commonly

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[1] LINDA also contains information about the household members of the sampled persons, as well as a special sample of immigrants to Sweden. However, we only use the random sample of the Swedish population, which of course also contains immigrants.

[2] The monthly earnings figures are expressed in full-time equivalents, i.e., they give the amount the individual would have earned had the individual worked full time.

[3] We use seven levels of education. Ed1: less than nine years of education (*folkskola* and incomplete comprehensive school, *grundskola*). Ed2: nine or ten years of basic education, i.e. comprehensive school (*grundskola*) or junior secondary school (*realskola*). Ed3: upper secondary school for up to two years (*kortare gymnasium*). Ed4: upper secondary school (high school) for three years (*längre gymnasium*). Ed5: post secondary schooling for less than three years (*kortare universitetsutbildning*). Ed6: at least three years of post secondary education (*längre universitetsutbildning*). Ed7: completed doctoral degree (*forskarutbildning*).

[4] For more information, see Statistics Sweden (1992).

used in previous research. It contains information about a number of central determinants of individuals' wages. In addition to human capital variables like schooling[6], work experience and tenure, the dataset provides information about self-reported working conditions as well as several demographic characteristics. The hourly wage is measured using information from a sequence of questions. A question is first asked about the mode of pay, whether it is by hour, by week, by month, by piece rate, etc. Conditional on the answer to this question, the next question is about the pay per hour, per week etc. Finally, information about normal working hours is used to compute hourly wages for those who are not paid by hour.

For our purposes, the drawback of the SLLS is its small sample size. The survey is basically a representative sample of one per thousand of the population aged 15-75 years (18-75 in 1991) in each year. This yields roughly 3,000 observations of employed male and female workers in each year.

Table 1 summarizes the five different samples that we use. The data from the three waves of the SLLS show that the raw gender log wage differential declined from 0.33 in 1968 to 0.18 in 1981 and then rose somewhat to 0.20 in 1991. All wages are in nominal terms. Note that SLLS and SSW wage data are expressed in different units, namely hourly and monthly, respectively. The well-known overall wage compression that took place during the 1970's is also demonstrated by the fact that both the standard deviation of the log wage and the 90/10 percentile ratio fell sharply from 1968 to 1981 for both men and women. That the 90/50 and 50/10 percentile ratios declined as well shows that the compression took place in both parts of the wage distribution.

In terms of explanatory variables in the SLLS data, there are almost no gender differences in years of schooling but, as expected, men have more work experience than women, even though the differential is falling over time. Further, men more often work full time and in the private sector.

The data from Statistics Sweden show a smaller raw wage gender differential in the early 1990's - : 0.15 in 1992 compared to 0.20 in the 1991 wave of the SLLS. Further, both the standard deviation of the log wage and the percentile ratios reveal less wage

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[5] For more information, see Erikson and Åberg (1987).

[6] The 1991 SLLS data also contains information on education from Statistics Sweden's education register.

inequality in the SSW data. Even though there is a year and a half between the data collection points – the SLLS data were collected in the spring of 1991 and the SSW wages refer to the fall of 1992 – the differences are more likely due to differences in measurement than to changes in the real wage structure. It is hard to tell which wage data are more reliable.[7] Probably both data sources suffer from some kind of measurement error. We estimated wage equations with identical regressors, and found that the explanatory power is somewhat higher in the SSW data (Appendix). This finding, together with the lower wage inequality in the SSW data, is consistent with lower classical measurement error in these data.

From 1992 to 1998, earnings inequality increased in all dimensions reported in the table. The gender gap rose to 0.16 and the standard deviation of log wages as well as the P90/P50 and P50/P10 ratios rose for both men and women. Further, the educational level rose over the 1990s, so that a larger fraction of women than of men had long university training (level 6) in 1998.

3. Basic Log Wage Gaps -- Figures

In this section, we present a series of figures that illustrate our basic findings. Our main finding is that the gender wage gap in Sweden is significantly larger at the top of the distribution than at the bottom. We interpret this as suggestive of a glass ceiling. This pattern is characteristic of the 1990's. A similar pattern, although not as pronounced, is present in 1981, but data from 1968 do not show this pattern. We also investigate the immigrant-nonimmigrant wage gap in Sweden in 1998, but find that the gap is essentially constant throughout the distribution. We interpret this as evidence that our finding of a gap that increases as one moves up the wage distribution is specifically a gender-related phenomenon. Finally, this phenomenon seems to be much more important in Sweden than it is in the U.S

Figure 1, which is based on the 1998 data, shows the gender log wage gap at each percentile in the wage distribution. Thus, for example, at the 75th percentile, we see a gender wage gap of slightly less than 20%. That is, the log wage of the man at the 75th

[7] Note that both the SSW and the SLLS data exclude the self-employed.

percentile of the male wage distribution is a bit less than 20 points above the log wage of the female at the 75th percentile of the female wage distribution.

The important features of this figure are (i) male and female wages are close to equal at the bottom of the wage distribution, (ii) male and female wages are extremely unequal (up to a maximum difference of about 40%[8]) at the top of the distribution, (iii) there is a steady increase in the gender log wage gap as we move up in the wage distribution, and (iv) there is a sharp acceleration in the increase in the gender log wage gap starting at about the 75th or 80th percentile in the wage distribution. It is this final aspect of the gender log wage gap by percentile that we interpret as a glass ceiling.

The same basic patterns can be seen in the 1992 wage distribution (Figure 2). This figure is based on a 1% sample from the 1992 SSW dataset. Relative to 1998, the 1992 data show a bit less overall inequality but a slightly stronger glass ceiling effect. Figure 3 shows the gender gap by percentile using the 1968, 1981, and 1991 SLLS datasets. The same basic patterns can also be seen in the 1991 SLLS dataset, although there are a few notable differences; namely, there is a bit more inequality between men and women at the bottom of the distribution, a bit less inequality at the top of the distribution, and a later (around the 87th percentile) breakpoint for the strong acceleration in male/female wage inequality. The pattern observed for the 1981 wage distribution is different. The log wage gap increases as we move up the distribution, but the sharp acceleration in the gap that we interpret as a glass ceiling effect is not present. Finally, in 1968, the nature of the gender wage gap is strikingly different. In that year, the most important gap between men and women is at the bottom of their respective distributions. It should be noted that the gender wage gaps shown in Figure 3 are based on many fewer observations than are the corresponding gaps in Figures 1 and 2.

The patterns we see in Figures 1-3 are consistent with the history of wage equalization efforts by Swedish unions. Centrally determined wage agreements contained clauses giving extra wage increases to members with low wages (Hibbs and Locking, 1996). These efforts were particularly strong during the 1970's and continued into the mid-1980's, and the decrease in the gender gap in the bottom of the distribution from 1968 through the early 1990's is consistent with a general attempt at wage compression.

[8] Note that a log wage gap of .4 is equivalent to a raw wage gap of about 50%.

To understand the spreading in the gender gap at the top of the distribution, one might also look for a general cause. One such cause might be that the Swedish labor market is discriminatory at the top in general, but, as Figure 4 shows, the immigrant log wage gap does not expand at the top of the distribution.[9] Instead this gap is essentially constant across all percentiles. Thus, it appears that the glass ceiling effect is a gender effect.

To put the 1990's patterns in the Swedish gender gap in perspective, it is useful to compare them with the corresponding U.S. patterns. Figure 5 gives the U.S. gender log wage gap by percentile as observed in the March 1999 Current Population Survey.[10] For most percentiles, the gender log wage gap is larger in the U.S. than in Sweden (as one would expect, since the percentage difference between average male and female wages is larger in the U.S. than in Sweden), but the gender log wage gap is very much larger in Sweden than in the U.S. at the top of the wage distribution. The strong dip in the gender log wage gap at the bottom of the distribution is likely attributable to the minimum wage; the dip at the very top of the distribution is probably caused by top-coding. Top-coding appears to affect fewer than 1% of the individuals in the CPS, but this 1% figure will understate the problem if most of the top-coding applies to wages paid to males, as one would expect. However, if we look at the 75th through the 90th percentile, the figure differs greatly from the Swedish pattern.

Our Figure 5 is comparable to Figure 2a in Fortin and Lemieux (1998). They used data from the outgoing rotation groups in the 1991 Current Population Surveys on individuals' usual weekly or hourly earnings from their main jobs for their analysis. Note that Fortin and Lemieux used hours-weighted wages, whereas our wages are unweighted. Nonetheless, the pattern shown in Fortin and Lemieux (1998) is essentially the same as that shown in Figure 5. We interpret these graphs as indicating that the glass ceiling effect is stronger in Sweden than in the U.S.

What factors might account for the patterns observed in Figures 1-3? A first potential explanation is a compositional one. During the 1970's and early 1980's, average labor market prospects improved for women relative to men. This implies that the average log wage gap between older men and older women in the 1990's is larger than

[9] We define an immigrant to be someone not born in Sweden and who came to Sweden in 1987 or later. The result shown in Figure 4 does not appear to be sensitive to changes in the definition of immigrant.
[10] Wages are computed as usual weekly earnings divided by usual weekly hours.

the corresponding gap for younger men and younger women. Since wages increase with experience, older workers will tend on average to have higher wages than younger workers. The combination of these two factors could generate an upward-sloping gender log wage gap.

The gender log wage gaps for various cohorts are illustrated in Figure 6. The lowest profile is for the youngest cohort of workers in the 1998 data, namely, those between the ages of 18 and 33. The other two profiles, those for workers aged 34-49 and 50-65, are very similar to each other and very different from the profile for the youngest workers in the upper tail of the distribution. Since the older workers are, on average, more highly paid than their younger counterparts, the fact that the latter two profiles lie above the one for the youngest cohort accounts for an increasing gender log wage gap. This effect, while potentially important, does not explain the sharp acceleration in the gender log wage gap that we see at the top of the 1990's distributions. Rather, this acceleration simply reflects the gender log wage profiles of the oldest two cohorts.[11] In addition, if composition explained the glass ceiling effect in Sweden, then one would expect it to also produce a glass ceiling effect in the U.S. data, where average wages for women relative to those for men have also increased over time. Since the U.S. pattern is so different from the Swedish pattern, the compositional argument does not seem compelling.

Another explanation could be that men and women differ in terms of characteristics that are rewarded in the labor market. Table 1 suggests four differences that are worth investigating. First, men typically have more years of work experience than women (e.g., an average of 20.1 years of work experience for men versus 16.8 years for women in the 1991 SLLS data). Unfortunately, we lack a direct measure of experience in the SSW data. Second, men are much more likely than women to work in the private sector. In the 1998 SSW data, 72.0% of the men versus 39.3% of the women work in the private sector. Third, men are more likely to work full time than women are. In the 1998 SSW data, using a definition of full time as working 32 hours or more per

[11] The fact that the gender log wage gap does not accelerate in the upper tail of the distribution for the youngest cohort might be taken as evidence that these workers do not face a glass ceiling, but, of course, one must take into account that younger workers are in the early part of their careers before age-earnings profiles typically fan out.

week, 96.2 % of men versus 85.2% of women work full time. Fourth, and finally, although male and female educational attainments are essentially the same in terms of years of schooling, there are some potentially important differences in the types of education completed by men and women. For example, men are much more likely than women to have completed a doctoral degree. To examine the effects of differences between men and women on the gender log wage gap at different points in the distribution, we present a series of quantile regressions in the next section.

A final explanation, which we also pursue in the next section, is that the rewards for various labor market characteristics differ between women and men.

4. **Quantile Regression Results**

In this section, we present a series of quantile regressions to investigate the extent to which the gender log wage gap at various percentiles can be explained by differences in labor market characteristics between men and women. We also estimate separate quantile regressions for men and for women to examine the extent to which the returns to the various labor market characteristics at various percentiles differ by gender. These regressions are based on the 1998 LINDA dataset.

Quantile regression[12] is a technique for estimating the q^{th} quantile of a variable (log wage in our application) conditional on covariates. The advantage of quantile regression over, say, ordinary least squares is that it allows one to estimate the marginal effect of a covariate on log wage at various points in the distribution, i.e., not just at the mean. Thus, for example, quantile regression allows us to estimate the effect of gender, age, education, etc. on log wage at the bottom of the log wage distribution (e.g., at the 10^{th} percentile), at the median, and at the top of the distribution (e.g., at the 90^{th} percentile).

The first panel of Table 2 presents a series of simple quantile regressions in which we condition log wage on gender at the 5^{th}, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th}, and 95^{th} percentiles. We also present the corresponding OLS regression for comparison. The coefficient estimates for the gender dummy in this panel are (necessarily) identical to the log wage gaps one could read off Figure 1. The advantage of quantile regression in this context is

[12] For a technical description of quantile regression, see Buchinsky (1994) and (1998).

that we can attach standard errors to the estimated gender log wage gaps at the various percentiles. These standard errors are estimated using bootstrap resampling, and the estimation procedure we use (sqreg in STATA 6.0) provides a bootstrapped estimate of the entire variance-covariance matrix of the estimators.

As we saw in Figure 1, the effect of gender on log wage increases as we move up the wage distribution with a particular acceleration after the 75th percentile. We tested pairwise equality of adjacent coefficients (e.g, equality of the gender dummies at the 5th and 10th percentiles), as well as an F-test for equality of all 7 gender dummies. The hypothesis of equality is overwhelmingly rejected (i.e., p-value $\approx$ 0) in all cases. Of course, this strengthens the point illustrated by Figure 1, namely, that just looking at the average gender log wage gap (16.2% -- the OLS estimate) is inadequate.

The next panel of Table 2 presents quantile regression estimates of the effects of age, age-squared, and education, as well as gender, on log wage at the various percentiles. We begin with these basic regressors for two reasons. First, age (at least when a direct measure of experience is unavailable) and education are the two variables that are universally used in log wage regressions. Second, these variables, unlike others such as number of children, sector, and full versus part time, are less tainted by possible endogeneity.

The gender dummies in these regressions are interpreted as the effects of gender on log wage at the various percentiles once we control for any differences in these basic labor market characteristics between genders. Interestingly, when we control for age and education, the gender dummy increases in absolute value relative to the raw gender dummy from the 5th through the 75th percentile. At the 90th and 95th percentiles, however, controlling for the basic regressors decreases the effect of gender.

It is also worth noting that the effect of age and age-squared on log wage is constant in the bottom half of the wage distribution. At the 75th percentile and beyond, the effect of age increases. The coefficients on the education dummies increase almost uniformly at each percentile with the level of education, and the effect of each education level on log wage is almost uniformly increasing as we move up the wage distribution.

Panel 3 of Table 2 presents the quantile log wage regression estimates using all of the relevant control variables that are available to us in the 1998 data. When we control for number of children (living at home, under age 18), sector (private, local government, and central government as the left-out category), full-time versus part-time work, and immigrant status, as well as for age, age-squared, and education category, we find that the gender dummy is reduced only minimally at the bottom of the wage distribution (e.g., 4.4% versus a raw gender effect of 4.8% at the 5th percentile) but more substantially at the top of the wage distribution (e.g., 21.2% versus a raw gender effect of 38.7% at the 95th percentile). Of course, number of children, sector of employment, and full-time versus part-time status are to some extent endogenous variables.

Including the other regressors does not substantially affect the patterns exhibited by the estimated coefficients on age, age-squared, and the education categories. The only difference worth noting is that when we control for sector, etc., the effects of lower levels of education become less important at the bottom of the wage distribution while the effects of higher levels of education become more important at the top of the wage distribution. In terms of the other regressors, the effect of an additional child is positive but quantitatively unimportant throughout the wage distribution. The effect of sector is much more important. Working in the private sector has a small negative effect (relative to working for the central government) at the bottom of the wage distribution, but at the top of the wage distribution there is a very strong private sector effect. Controlling for all other variables (including gender), the log wage gap between private sector workers at the 95th percentile versus central government workers at their 95th percentile is estimated to be 14.6%. Working in the local government sector is also quantitatively very important. The local government effect is uniformly negative and becomes more negative as we go up the wage distribution. The full-time dummy is positive at the bottom and middle of the wage distribution and negative (but quantitatively not very important) at the top of the distribution. Finally, the immigrant effect is negative throughout the wage distribution, somewhat more so at the bottom of the distribution. It is interesting to note that the immigrant effect controlling for other variables is substantially more negative than the raw effect of immigrant status, as can be seen from Figure 4.

In terms of explaining the gender log wage gap by differences in labor market characteristics between the genders, the essential message of Table 2 is quite clear. Except at the very top of the wage distribution, controlling for covariates does not account for much of the gap. Even at the 75th percentile, and even when we include variables that are arguably endogenous, we can explain less than 25% of the raw gender gap (19.8% versus 15.1%). At the 90th and 95th percentiles, matters are somewhat different. Using only age, age-squared, and education, we can explain about 21% (respectively, 24%) of the gender log wage gap at the 90th (respectively, 95th) percentiles. To put these figures in perspective, this is only slightly less than the fraction of the average gender log wage gap that can be explained using the OLS regression on the full set of covariates (12.2% versus 16.2%). Of course, once we include sector, etc. as regressors, we can reduce the coefficient on the gender dummy at the 90th and 95th percentiles even further.

Tables 3 and 4 present quantile log wage regressions by gender. In Table 3, we estimate the effects of age, age-squared and education on log wage separately for men and for women at the various percentiles. In Table 4, we repeat the exercise using our full set of covariates. To save space in Table 4, we present only our estimates for the 10th, 50th, and 90th percentiles, but the estimated standard errors are based on the complete estimation across the full set of percentiles used in Tables 2 and 3. Our objective in these estimations is to examine the extent to which returns to labor market characteristics differ between men and women at the various points in their respective distributions.

With respect to age, the coefficients for men are always above the corresponding coefficients for women, and this gap grows as we move up the wage distribution. This is due in part to the fact that age is a better proxy for experience for men than for women and in part to the fact that women's log wage-experience profiles tend to be flatter than men's, even when a good measure of experience is available. In addition, the coefficient on age is higher for both men and women (in both Tables 3 and 4) at the top of the wage distribution.

In terms of education, women realize a slightly higher return than men do at almost all levels of education at the very bottom of the wage distribution. In Table 3, once we reach the 25th percentile, men start to get a bigger payoff than women do at almost all levels of education. This is particularly true at the very top of the wage distribution. For some levels of education, this difference is quite important. For example, holding age constant, at the respective 95th percentile points in the two distributions, the payoff to a man who has completed at least three years of post-secondary schooling (Ed6) is estimated to be about 18% higher (i.e., 0.769-0.588) than the corresponding payoff to a women. Interestingly, however, the payoffs to doctoral degrees (Ed7) do not seem to be much different between men and women.

The patterns in Table 4 are similar. In terms of the additional variables, it is worth noting that the premium for working in the private sector is much higher for men than for women throughout the wage distribution, the penalty associated with local government employment is greater for men at the bottom of the distribution but lower at the 90th percentile, the full-time premium is consistently larger for men, and, finally, the decrease in log wage associated with immigrant status is much greater for men than for women.

5. Conclusions

In this paper, we have addressed the question of whether there is a significant glass ceiling on women's wages in Sweden. The answer, quite simply, is yes. There is an extremely large gap between men and women at the top of the wage distribution. The size of this gap is especially striking given the fact that the average gender log wage gap in Sweden is quite small by international standards. It is also the case that this glass ceiling phenomenon is not diminishing over time – on the contrary, we find that the glass ceiling is much more pronounced in the 1990's than it was earlier. We also find that the glass ceiling is much more important in Sweden than in the U.S., which is perhaps contrary to what one might expect given the fact that the Swedish average log wage gap between the genders is smaller than the corresponding U.S. gap. Finally, we examine the log wage gap for non-immigrants versus immigrants. The fact that this gap does not increase as we move up the wage distribution suggests that the glass ceiling effect is specifically related to gender, as opposed being to a more general labor market phenomenon.

We next examine the extent to which the gender gap at various percentiles in the wage distribution can be explained by differences in the characteristics that men and women bring to the labor market. Using quantile regressions, we find that covariates can account for some of the gap between males and females at the top of the wage distribution. However, a substantial fraction of the gap remains unexplained. We also estimated separate quantile regressions by gender and found substantial differences between the genders in the coefficients on the covariates at various percentiles in the male and female distributions. In the next version of this paper, we will carry out a decomposition analysis to determine the extent to which the log wage gap at various percentiles can be ascribed to differences between the genders in covariates, to differences in coefficients, and to a pure residual component.

Given that we have established the existence of a substantial glass ceiling effect, it is tempting to speculate about possible causes. The most obvious candidate is the collection of policies in Sweden that influence the interaction between work and family. Specifically, we have in mind Swedish parental leave policy and the daycare system. Essentially, these policies give Swedish women (and men, in principle) a strong incentive to participate in the labor force. The benefits that a new parent can obtain when a child is born are strongly conditioned on that parent’s employment history, and access to the daycare system is (essentially) conditioned on labor force participation. At the same time, the benefits built into Swedish policy may discourage strong career commitment on the part of the parents who are most involved in child rearing. In practice, this means that women may have strong incentives to participate in the labor force but not to do so very intensively. This policy effect may be compounded by employers, who presumably would expect less career commitment from their female employees. As a result, women may choose (or be tracked into) the less demanding jobs. The outcome would then be one in which women do well relative to men at the bottom and middle of the wage distribution but fall substantially behind at the top of the distribution.

Table 1. Sample Means. Standard deviations in parentheses

	SLLS-1968		SLLS-1981		SLLS-1991		SSW-1992		SSW-1998	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Ln wage	2.41 (0.442)	2.07 (0.470)	3.66 (0.308)	3.48 (0.276)	4.44 (0.312)	4.24 (0.241)	9.64 (0.286)	9.49 (0.194)	9.87 (0.320)	9.71 (0.223)
P90/P10	2.59	2.46	1.97	1.65	2.05	1.71	1.96	1.56	2.13	1.63
P90/P50	1.73	1.63	1.63	1.34	1.54	1.38	1.55	1.32	1.65	1.35
P50/P10	1.50	1.51	1.28	1.23	1.33	1.24	1.26	1.18	1.29	1.21
Age	39.9	38.4	39.2	38.6	39.7	39.6	40.1	41.2	41.1	41.9
Years of work exp.	23.0	14.7	20.6	15.2	20.1	16.8	n.a.	n.a.	n.a.	n.a.
Years of schooling	8.6	8.7	10.7	10.3	11.7	11.5	n.a.	n.a.	n.a.	n.a.
Full time	0.968	0.610	0.926	0.520	0.94	0.593	-	-	0.962	0.852
Private Sector	0.762	0.559	0.703	0.403	0.705	0.389	0.727	0.393	0.720	0.393
Ed1	n.a.	n.a.	n.a.	n.a.	0.141	0.111	0.140	0.120	0.088	0.064
Ed2	n.a.	n.a.	n.a.	n.a.	0.110	0.117	0.115	0.114	0.119	0.103
Ed3	n.a.	n.a.	n.a.	n.a.	0.358	0.409	0.335	0.396	0.317	0.350
Ed4	n.a.	n.a.	n.a.	n.a.	0.153	0.116	0.153	0.099	0.190	0.148
Ed5	n.a.	n.a.	n.a.	n.a.	0.116	0.135	0.121	0.147	0.140	0.176
Ed6	n.a.	n.a.	n.a.	n.a.	0.108	0.108	0.124	0.120	0.132	0.153
Ed7	n.a.	n.a.	n.a.	n.a.	0.014	0.004	0.012	0.003	0.013	0.005
# of obs	1 898	1 196	1 824	1 659	1 655	1 663	14 582	15 155	49780	48407

Table 2. Quantile Log Wage Regressions: Bootstrapped Standard Errors in Parentheses

	5th Percentile	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile	95th Percentile	OLS
Panel 1								
Gender Dummy	-.048 (.0015)	-.065 (.0016)	-.098 (.0018)	-.133 (.0019)	-.198 (.0036)	-.336 (.0050)	-.387 (.0060)	-.162 (.0018)
Constant	9.473 (.0007)	9.548 (.0010)	9.663 (.0015)	9.804 (.0015)	10.012 (.0028)	10.307 (.0045)	10.494 (.0048)	9.870 (.0012)
Panel 2								
Gender Dummy	-.057 (.0027)	-.077 (.0019)	-.115 (.0017)	-.158 (.0018)	-.212 (.0019)	-.267 (.0024)	-.294 (.0053)	-.175 (.0015)
Age	.025 (.0008)	.025 (.0005)	.025 (.0005)	.025 (.0006)	.033 (.0008)	.035 (.0011)	.039 (.0013)	.030 (.0005)
Age Squared	-.0002 (.000009)	-.0002 (.000006)	-.0002 (.000005)	-.0002 (.000007)	-.0003 (.000009)	-.0003 (.000012)	-.0004 (.000014)	-.0003 (.000006)
Ed2	.015 (.0063)	.018 (.0042)	.038 (.0022)	.056 (.0025)	.082 (.0035)	.129 (.0080)	.167 (.0102)	.071 (.0037)
Ed3	.057 (.0056)	.055 (.0031)	.068 (.0019)	.080 (.0031)	.090 (.0051)	.113 (.0072)	.141 (.0091)	.091 (.0032)
Ed4	.062 (.0060)	.069 (.0037)	.102 (.0026)	.140 (.0036)	.193 (.0051)	.266 (.0071)	.326 (.0079)	.172 (.0035)
Ed5	.134 (.0059)	.144 (.0040)	.174 (.0028)	.209 (.0035)	.254 (.0048)	.326 (.0096)	.384 (.0136)	.237 (.0035)
Ed6	.215 (.0060)	.232 (.0039)	.279 (.0021)	.341 (.0029)	.454 (.0060)	.590 (.0096)	.666 (.0116)	.393 (.0035)
Ed7	.337 (.0215)	.408 (.0125)	.488 (.0059)	.585 (.0118)	.702 (.0141)	.786 (.0188)	.781 (.0365)	.596 (.0084)
Constant	8.862 (.0144)	8.905 (.0102)	9.001 (.0093)	9.087 (.0116)	9.123 (.0154)	9.146 (.0218)	9.145 (.0287)	8.996 (.0099)

Table 2. Quantile Log Wage Regressions: Bootstrapped Standard Errors in Parentheses

	5th Percentile	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile	95th Percentile	OLS
Panel 3								
Gender Dummy	-.044 (.0026)	-.059 (.0018)	-.079 (.0014)	-.108 (.0015)	-.151 (.0023)	-.189 (.0083)	-.212 (.0051)	-.122 (.0016)
Age	.024 (.0008)	.024 (.0007)	.024 (.0005)	.025 (.0004)	.028 (.0010)	.031 (.0013)	.032 (.0017)	.028 (.0005)
Age Squared	-.0002 (.000009)	-.0002 (.000008)	-.0002 (.000005)	-.0002 (.000005)	-.0003 (.000012)	-.0003 (.000015)	-.0003 (.000021)	-.0003 (.000006)
Ed2	.007 (.0045)	.016 (.0018)	.035 (.0024)	.057 (.0029)	.082 (.0062)	.124 (.0076)	.160 (.0124)	.074 (.0036)
Ed3	.041 (.0042)	.052 (.0021)	.071 (.0018)	.090 (.0027)	.113 (.0047)	.144 (.0047)	.164 (.0089)	.106 (.0031)
Ed4	.053 (.0045)	.069 (.0028)	.101 (.0031)	.141 (.0043)	.196 (.0059)	.267 (.0051)	.316 (.0090)	.178 (.0034)
Ed5	.121 (.0047)	.142 (.0030)	.184 (.0025)	.233 (.0029)	.285 (.0046)	.351 (.0040)	.395 (.0090)	.265 (.0034)
Ed6	.196 (.0049)	.229 (.0032)	.290 (.0028)	.371 (.0039)	.481 (.0059)	.628 (.0075)	.719 (.0123)	.428 (.0035)
Ed7	.323 (.0220)	.397 (.0146)	.492 (.0095)	.612 (.0122)	.743 (.0194)	.870 (.0215)	.944 (.0201)	.636 (.0082)
No. of Children	.003 (.0010)	.004 (.0009)	.006 (.0008)	.006 (.0010)	.009 (.0013)	.010 (.0023)	.012 (.0027)	.009 (.0008)
Private	-.031 (.0034)	-.012 (.0029)	.020 (.0023)	.047 (.0017)	.086 (.0035)	.130 (.0053)	.146 (.0102)	.066 (.0024)
Local Gov.	-.028 (.0023)	-.032 (.0018)	-.040 (.0018)	-.057 (.0014)	-.069 (.0023)	-.077 (.0042)	-.106 (.0079)	-.058 (.0026)
Full-Time Dummy	.069 (.0035)	.061 (.0020)	.051 (.0017)	.039 (.0016)	.015 (.0026)	-.010 (.0039)	-.016 (.0040)	.048 (.0020)
Immigrant Dummy	-.145 (.0086)	-.141 (.0069)	-.132 (.0053)	-.105 (.0064)	-.097 (.0090)	-.092 (.0130)	-.101 (.0173)	-.129 (.0049)
Constant	8.860 (.0165)	8.895 (.0146)	8.949 (.0088)	9.009 (.0081)	9.048 (.0182)	9.098 (.0237)	9.160 (.0320)	8.913 (.0106)

Table 3. Quantile Regressions By Gender: Bootstrapped Standard Errors in Parentheses

	5th Percentile	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile	95th Percentile	OLS
Men								
Age	.028 (.0009)	.029 (.0008)	.028 (.0006)	.031 (.0008)	.035 (.0009)	.047 (.0017)	.051 (.0024)	.035 (.0008)
Age Squared	-.0003 (.000010)	-.0003 (.000009)	-.0003 (.000007)	-.0003 (.000011)	-.0003 (.000012)	-.0004 (.000022)	-.0005 (.000030)	-.0003 (.000010)
Ed2	.009 (.0086)	.014 (.0048)	.040 (.0040)	.056 (.0055)	.110 (.0094)	.166 (.0151)	.223 (.0190)	.079 (.0057)
Ed3	.055 (.0072)	.056 (.0036)	.075 (.0034)	.091 (.0042)	.133 (.0083)	.176 (.0117)	.225 (.0156)	.109 (.0050)
Ed4	.063 (.0068)	.071 (.0041)	.110 (.0031)	.154 (.0049)	.251 (.0092)	.341 (.0139)	.413 (.0187)	.199 (.0052)
Ed5	.124 (.0089)	.143 (.0056)	.198 (.0044)	.243 (.0048)	.332 (.0069)	.439 (.0129)	.499 (.0163)	.279 (.0055)
Ed6	.207 (.0098)	.227 (.0056)	.289 (.0064)	.418 (.0076)	.609 (.0062)	.703 (.0127)	.769 (.0140)	.456 (.0055)
Ed7	.342 (.0260)	.410 (.0118)	.490 (.0105)	.586 (.0188)	.720 (.0205)	.796 (.0353)	.809 (.0491)	.604 (.0114)
Constant	8.785 (.0190)	8.833 (.0179)	8.908 (.0109)	8.931 (.0128)	8.908 (.0187)	8.764 (.0323)	8.727 (.0482)	8.836 (.0159)
Women								
Age	.021 (.0009)	.022 (.0007)	.022 (.0006)	.020 (.0005)	.023 (.0008)	.027 (.0014)	.032 (.0021)	.024 (.0006)
Age Squared	-.0002 (.000011)	-.0002 (.000008)	-.0002 (.000007)	-.0002 (.000006)	-.0002 (.000009)	-.0003 (.000017)	-.0003 (.000024)	-.0002 (.000007)
Ed2	.019 (.0082)	.024 (.0056)	.038 (.0048)	.059 (.0055)	.072 (.0068)	.097 (.0088)	.115 (.0116)	.063 (.0045)
Ed3	.059 (.0044)	.056 (.0039)	.065 (.0033)	.074 (.0041)	.070 (.0054)	.072 (.0086)	.072 (.0097)	.073 (.0039)
Ed4	.064 (.0046)	.071 (.0049)	.097 (.0042)	.125 (.0059)	.142 (.0065)	.181 (.0113)	.225 (.0131)	.133 (.0044)
Ed5	.138 (.0051)	.149 (.0046)	.162 (.0035)	.187 (.0042)	.211 (.0051)	.244 (.0083)	.280 (.0133)	.195 (.0042)
Ed6	.218 (.0075)	.236 (.0045)	.272 (.0040)	.309 (.0044)	.333 (.0058)	.458 (.0121)	.588 (.0187)	.329 (.0042)
Ed7	.323 (.0221)	.379 (.0472)	.481 (.0183)	.605 (.0162)	.687 (.0223)	.771 (.0214)	.802 (.0897)	.595 (.0129)
Constant	8.867 (.0170)	8.896 (.0144)	8.961 (.0120)	9.059 (.0109)	9.122 (.0188)	9.147 (.0294)	9.133 (.0481)	9.008 (.0115)

Table 4. Quantile Regressions By Gender: Bootstrapped Standard Errors in Parentheses

	Men				Women			
	10th Percentile	50th Percentile	90th Percentile	OLS	10th Percentile	50th Percentile	90th Percentile	OLS
Age	.025 (.0007)	.028 (.0011)	.039 (.0019)	.031 (.0009)	.022 (.0006)	.021 (.0005)	.024 (.0015)	.025 (.0006)
Age Squared	-.0002 (.000008)	-.0002 (.000014)	-.0003 (.000025)	-.0003 (.000011)	-.0002 (.000007)	-.0002 (.000006)	-.0002 (.000018)	-.0002 (.000007)
Ed2	.015 (.0055)	.064 (.0041)	.158 (.0136)	.084 (.0055)	.021 (.0033)	.058 (.0042)	.094 (.0092)	.064 (.0043)
Ed3	.052 (.0046)	.099 (.0035)	.176 (.0124)	.115 (.0048)	.050 (.0022)	.088 (.0029)	.118 (.0055)	.090 (.0038)
Ed4	.072 (.0049)	.175 (.0044)	.343 (.0099)	.211 (.0051)	.066 (.0045)	.120 (.0033)	.175 (.00733)	.132 (.0043)
Ed5	.156 (.0051)	.279 (.0050)	.437 (.0135)	.311 (.0054)	.136 (.0037)	.211 (.0033)	.292 (.0060)	.219 (.0041)
Ed6	.248 (.0083)	.462 (.0055)	.737 (.0139)	.505 (.0054)	.219 (.0043)	.333 (.0033)	.479 (.0089)	.353 (.0041)
Ed7	.414 (.0231)	.639 (.0138)	.902 (.0281)	.673 (.0111)	.361 (.0308)	.601 (.0136)	.871 (.0351)	.597 (.0125)
No. of Children	.011 (.0012)	.012 (.0011)	.015 (.0030)	.014 (.0013)	-.003 (.0011)	-.001 (.0009)	.000 (.0021)	-.001 (.0010)
Private	.009 (.0033)	.080 (.0029)	.160 (.0073)	.097 (.0036)	-.038 (.0034)	.021 (.0031)	.099 (.0079)	.030 (.0030)
Local Gov.	-.053 (.0036)	-.072 (.0036)	-.073 (.0103)	-.071 (.0044)	-.032 (.0027)	-.057 (.0029)	-.108 (.0085)	-.062 (.0029)
Full-Time Dummy	.125 (.0057)	.102 (.0038)	.066 (.0117)	.113 (.0047)	.042 (.0020)	.029 (.0019)	-.016 (.0036)	.034 (.0019)
Immigrant Dummy	-.159 (.0107)	-.140 (.0081)	-.126 (.0110)	-.156 (.0077)	-.113 (.0076)	-.076 (.0073)	-.062 (.0121)	-.094 (.0057)
Constant	8.794 (.0133)	8.818 (.0200)	8.700 (.0289)	8.722 (.0170)	8.910 (.0140)	9.030 (.0125)	9.179 (.0310)	8.970 (.0121)

Appendix:

Table A1. Estimated wage equations using data from SLLS-91 and SSW-92 with identical regressors. Standard errors in parentheses.

	SLLS-91			SSW-92		
	All	Men	Women	All	Men	Women
Constant	3.561 (0.047)	3.359 (0.075)	3.565 (0.056)	8.874 (0.014)	8.702 (0.024)	8.904 (0.015)
Age	0.031 (0.002)	0.038 (0.004)	0.025 (0.003)	0.026 (0.001)	0.032 (0.001)	0.020 (0.001)
Age sq./1000	-0.296 (0.028)	-0.353 (0.046)	-0.246 (0.034)	-0.247 (0.008)	-0.297 (.014)	-0.192 (.009)
Ed2	0.070 (0.018)	0.101 (0.028)	0.047 (0.022)	0.077 (0.005)	0.100 (0.008)	0.057 (0.005)
Ed3	0.121 (0.014)	0.161 (0.022)	0.087 (0.018)	0.100 (0.004)	0.123 (0.007)	0.080 (0.004)
Ed4	0.192 (0.017)	0.226 (0.025)	0.140 (0.023)	0.175 (0.005)	0.210 (0.007)	0.119 (0.006)
Ed5	0.273 (0.017)	0.307 (0.027)	0.242 (0.021)	0.223 (0.005)	0.248 (0.008)	0.199 (.005)
Ed6	0.365 (0.017)	0.377 (0.027)	0.353 (0.022)	0.385 (0.005)	0.424 (0.008)	0.346 (0.005)
Ed7	0.444 (0.045)	0.444 (0.057)	0.475 (0.085)	0.581 (0.014)	0.593 (0.018)	0.567 (0.023)
Woman	-0.195 (0.008)	-	-	-0.154 (0.002)	-	-
# of obs	3312	1653	1658	28 976	14 231	14 744
Adj. R-sq.	0.347	0.278	0.273	0.398	0.337	0.414

Note: Educational levels are presented in the text. Ages: 18-65 years.

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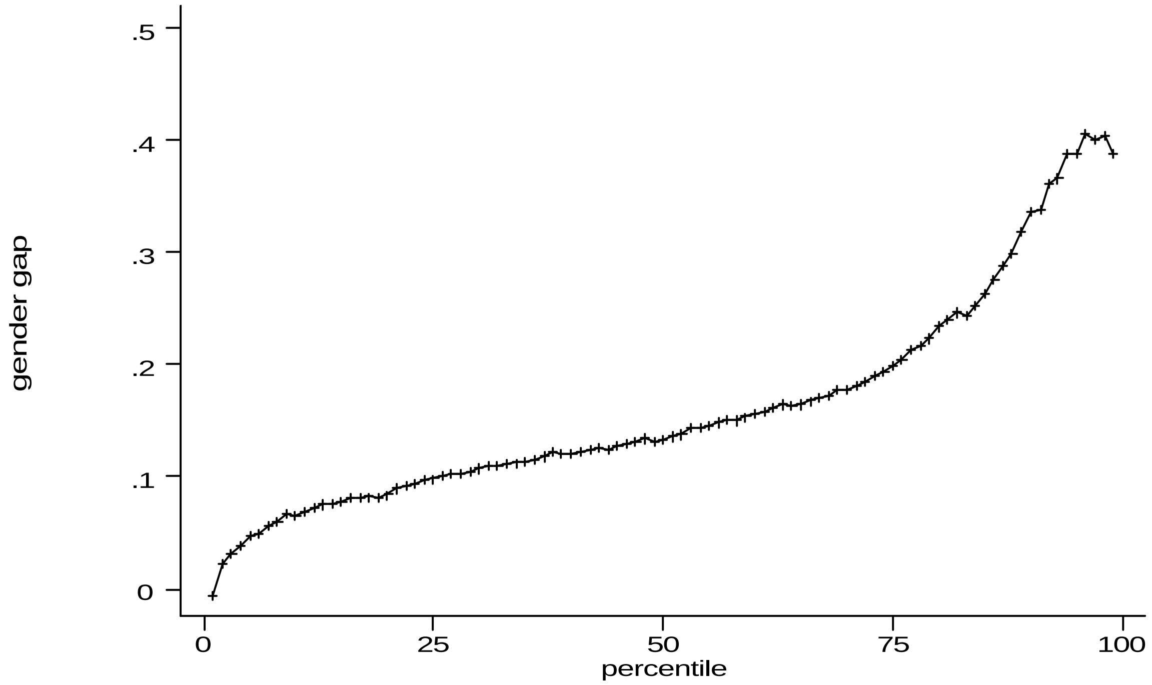

Figure 1: Gender Log Wage Gap, Sweden 98

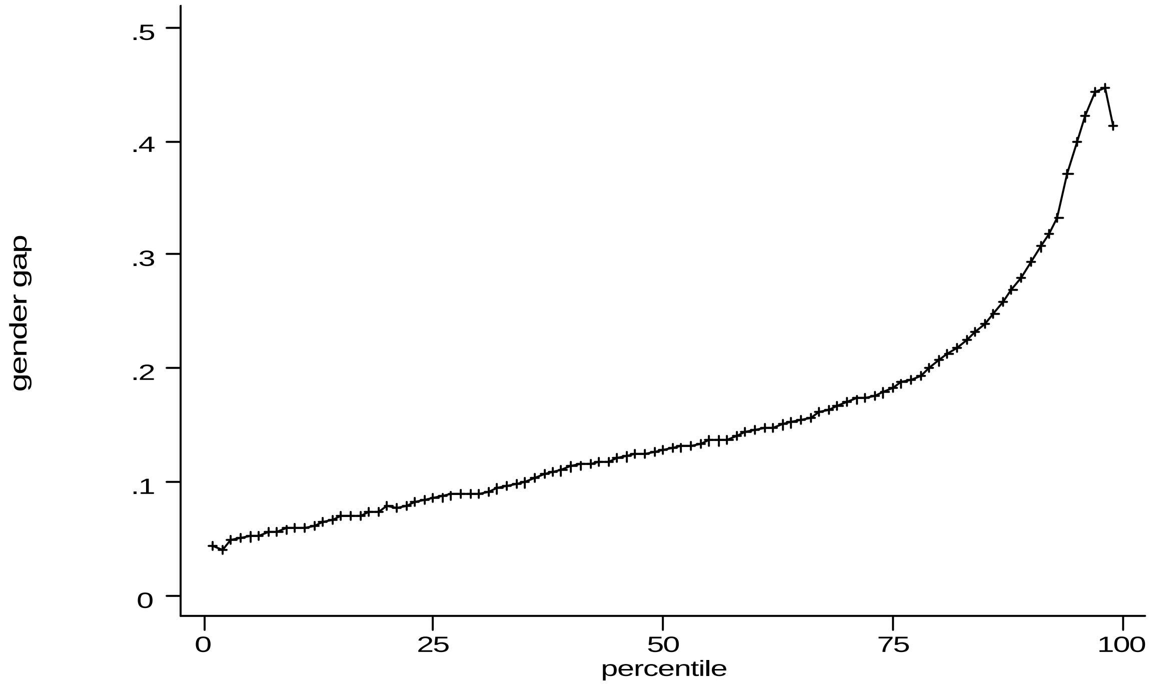

Figure 2: Gender Log Wage Gap, Sweden 92

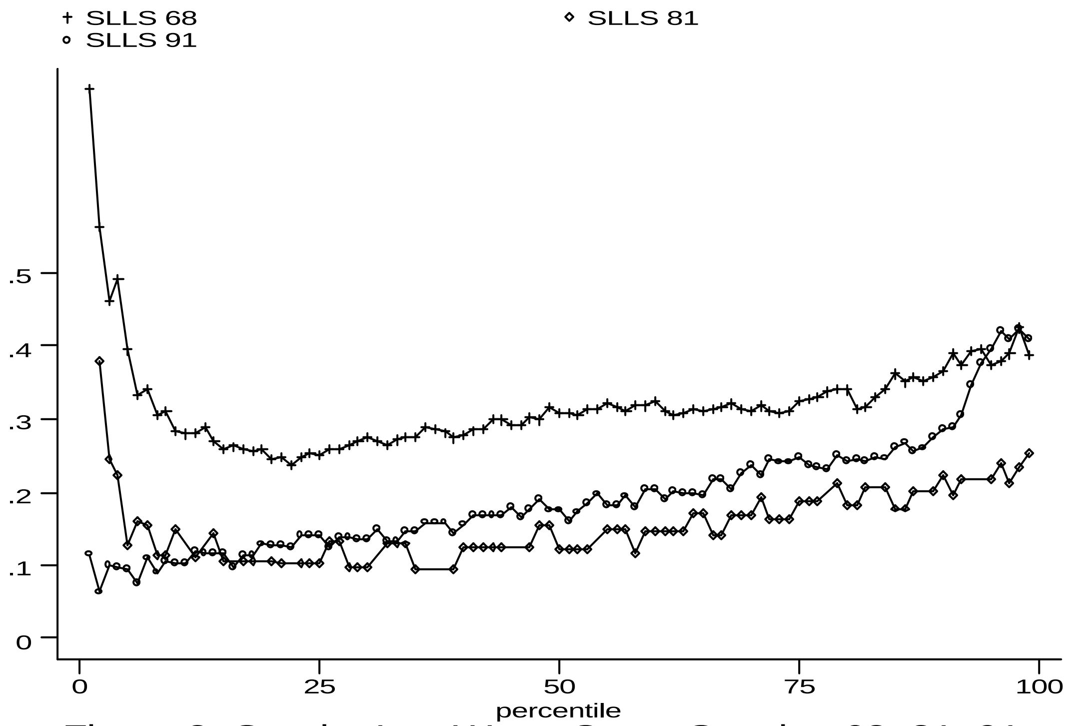

Figure 3: Gender Log Wage Gaps, Sweden 68, 81, 91

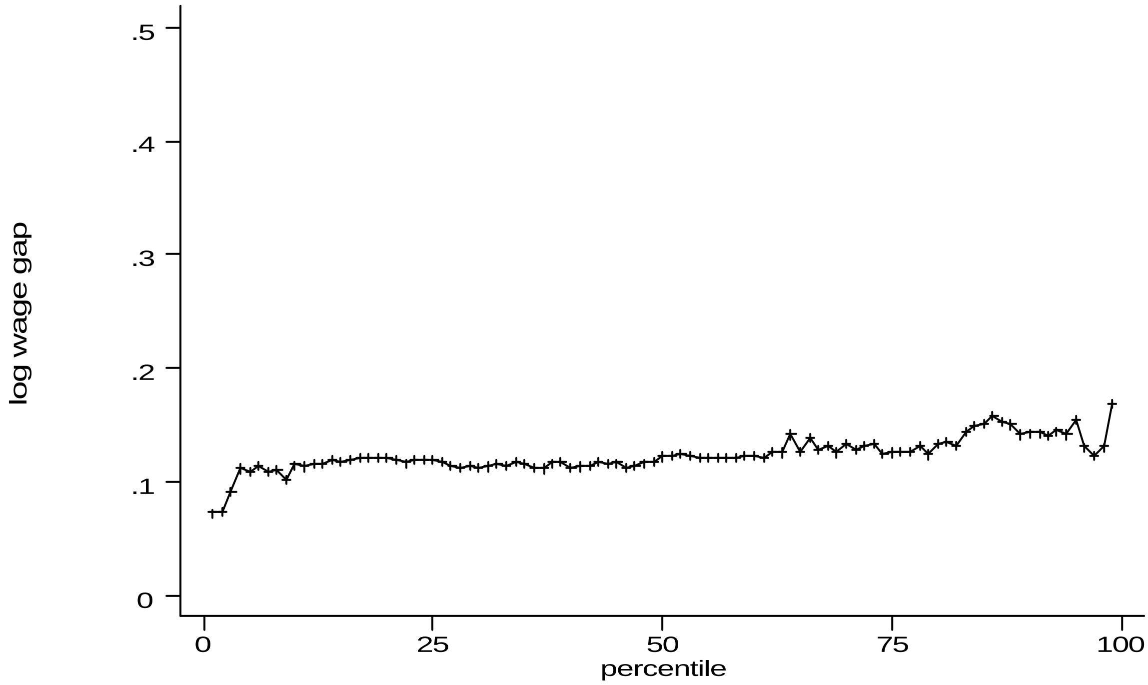

Figure 4: Immigrant Log Wage Gap, Sweden 98

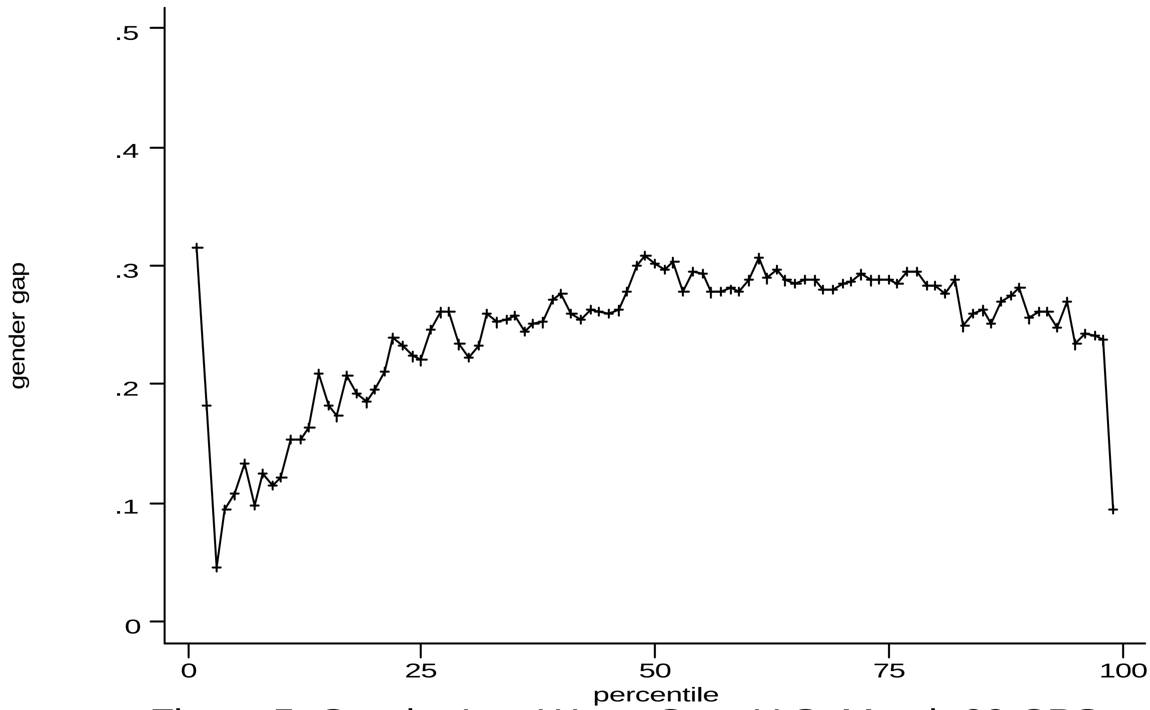

Figure 5: Gender Log Wage Gap, U.S. March 99 CPS

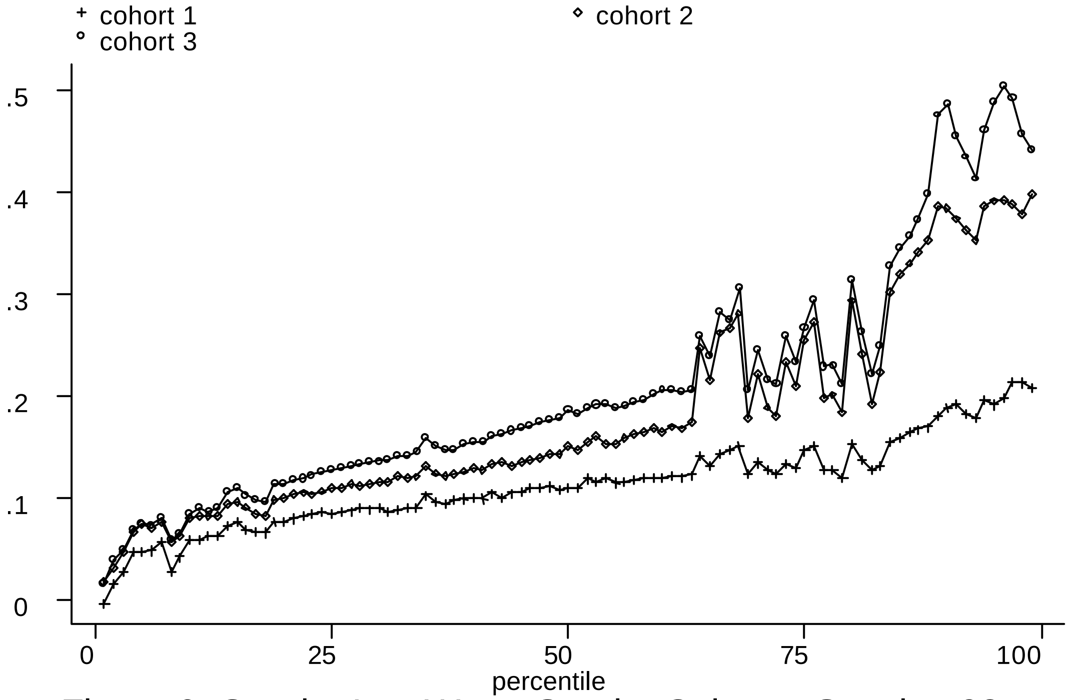

Figure 6: Gender Log Wage Gap by Cohorts, Sweden 98