The Labor Market Gender Gap in Denmark: Sorting Out the Past 30 Years *

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Abstract

We document the declining gap between the average earnings of women and men in Denmark from 1980 to 2010. The decline in the earnings gap is driven by increased labor force participation and increases in hours worked by women, and to a smaller extent by a decline in the gender wage gap. The gap has declined least among higher earning women—the average wage of the top 10 percent of female earners is 28-33% lower than the average wage of the top 10 percent of male earners. Women are becoming more educated and are a larger share of the professional labor force than in previous decades, but a substantial wage gap of about 10 percent remains for the youngest cohorts even after controlling for age, education, experience, occupation, and firm choice. Unlike the case of the US, differences in educational attainment, occupational choice, industry, and experience explained about 15 percentage points of the Danish wage gap in 1980, but now these factors explain only about 6 percentage points of the Danish wage gap. In fact, though variation in the wage gap across occupations is substantial, this variation is not correlated with the fraction of the occupation which is female. The data show a great deal of sorting and segregation across industries, occupations, and even firms. However, this sorting does not explain more than half of the wage gap. We conclude that a great deal of the remaining disparity between the wages of women and men is tied to the differential effects of parenthood by gender.

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1 Introduction

Despite advances in labor force participation, educational attainment, and changes in the generosity of maternity benefits and inducements to return to work after having children, a gender wage gap of almost 20% persists in Denmark. This paper contributes to the literature by being the first to give an overview of women's labor market experience over a more than 30 year period. We document changes in the relative pay of women compared to men in Denmark from 1980 to 2010. We document gender differences in not only wages and earnings, but also in labor force participation, hours worked, and public sector work over this time period. In general, the wage gap has declined somewhat over time. However, the residual wage gap—that portion of the gap not attributable to observable characteristics—has not declined substantially since 1980.

In Denmark, the decline in the wage gap occurs both within and across cohorts, but most of the general reduction in the wage gap is experienced by younger women. Looking more closely to sources of the today's wage gap, we find that while there has been some convergence in the relative wage of men and women in the bottom of the wage distribution, there has been only a 5 percentage point change in the 33 percent gap between the highest earning 10% of men compared to the highest earning 10% of women. We then turn to understanding the sources of the wage gap and how differences in educational attainment, occupation choice, and industry choice have contributed to a wage gap over time. There is an extremely high degree of occupational sorting and industry sorting by gender. Despite substantial, persistent sorting by gender into occupations and industries, we find that occupation and industry choices explain a declining share of the wage gap.

Beginning with Becker's seminal model of employer discrimination (Becker [1971]), models explaining how a difference in wages may emerge between men and women which can't be explained by differences in education, experience, etc (Aigner and Cain [1977], Black [1995], Lang and Manove [2011]). Empirically, discrimination is more difficult to verify as any residual wage gap may arise from missing covariates (Altonji and Blank [1999]). Estimates of the residual wage gap depend a great deal on what controls are used in regressions[1]. Even imperfect

[1] O'Neill [2003] for example finds a very small wage gap in the US when including a host of controls from the NLSY, but some of these controls (such as child-related variables) may be choices reflecting discrimination in the labor market itself.

controls can illuminate the role of preferences relative to discrimination, however. If most of the wage gap can be attributed to the occupational choices of women, for example, then preferences likely play a huge role in the wage gap. In contrast, if the residual gap is large after controlling for workplace, occupation, and education choices, discrimination may play a large role in the labor market. Blau and Kahn [2016] study the evolution of the gender wage gap in the US over time. They find that occupation and industry choices explain an increasing fraction of the gap in the US, consistent with an increasing role for preferences over time.

In Denmark, gender wage gap in 2010 cannot easily be explained by age, occupation, industry, experience, or education differences between men and women. Together these variable explain only about six of the nineteen log point gender gap in wages, with industry differences playing the largest role in 2010. This contrasts with 1980 when about fifteen of the thirty log point difference could be explained by differences in these variables, particularly by occupation, industry, and experience. In recent years, sorting on industry and occupation explains even less of the gap in wages in the private sector where wage differences are larger between men and women.

As noted above, these results are different from the case of the US recently studied in Blau and Kahn [2016]. Using PSID data, Blau and Kahn [2016] perform a Oaxaca decomposition of the wage gap and find that the role of occupation has increased in 2010 compared to 1980. While we estimate that occupation explained 5.9 log points of the gender gap in Denmark in 1980, Blau and Kahn [2016] estimate that occupation explained 5.1 log points of the gender gap in the US in 1980. However, occupation explained 7.6 log points of the gap in the US in 2010 but only 3.1 log points of the gap in Denmark in the same year. In the US, the role of occupation has increased in explaining the gender wage gap. In Denmark, the role of occupation has decreased.

We next turn to understanding whether sorting across firms can explain some of the remaining wage gap, as suggested by Card et al. [2016] and Cardoso et al. [2016] using Portuguese data and Bayard et al. [2003] using US data. Bayard et al. [2003] regress wages on the fraction of an occupation which is female, the fraction of an industry which is female, and the fraction of an establishment which is female, and the fraction of an occupation within an establishment which is female, as well as other controls. Using data from the 1990 long-form US census matched with information on employers, they find that segregation explained about half of

the gender wage gap. Card et al. [2016] use Portuguese matched employer-employee data to study the role of firm-level sorting and firm-level bargaining in explaining the gender wage gap. They find that women are less represented at firms which offer high wage premiums and that this sorting effect explains about 15 % of the 23 log point wag gap, and another 5% of the gap can be attributed to women gaining less from working in high-wage firms (a "bargaining" effect).

When we specify firm and worker fixed effects in an AKM model as in Card et al. [2016], we find that establishment-level sorting explains less than one log point of the gender wage gap in the 1980s, but explains 2.7 log points of the gap in 2000s. The combined role of firm and occupational sorting is approximately constant over time and explains about 30 % of the log wage difference between men and women. What can explain the remaining wage gap in Denmark?

One explanation discussed in the literature is the role of motherhood. Very few women in Denmark drop out of the labor force after having children, and women change their career paths in response to having children. Nielsen et al. [2004] argue that Danish women select into the public sector precisely because there is little to no penalty for having children in that sector, estimating an endogenous switching model of career choice. Merlino et al. [2013] study the impact of children on differences in career advancement between men and women in Denmark and argue that women substantially change their career paths in order to accommodate children—gender differences in major promotions for mothers compared to fathers cause women to select into careers with less opportunity for advancement. Kleven et al. [2015] use an event study framework to describe the role of childbirth in explaining the gender earnings gap in Denmark. They find that motherhood plays a much larger role in explaining the gender earnings gap in 2010 compared to 1980, and that differences in hours worked, wages, and labor force participation explain equal parts of the "motherhood penalty." Using Swedish administrative data, Angelov et al. [2016] find that 15 years after the first child is born, the wage gap has increased by 10 percentage points. Bertrand et al. [2010] use detailed information on the career paths of MBA graduates and find that the gender gap in earnings increases over the lifecycle (reaching almost 60 log points after 10 years) career discontinuities and shorter work hours for female MBAs are largely associated with motherhood and explain a great deal of the gap. Thus, a potential explanation for the remaining wage and earnings gap in Denmark, is that having

children affects men and women differently in the labor market. We show that conditional on age men, who have had kids have higher wages and higher earnings, whereas the opposite is true for women. However, the wage and earnings penalty is declining for women comparing 2010 to 1980.

The remainder of this paper proceeds as follows: Section 2 describes the data used in calculations. Section 3 presents results first describing gender differences in labor market outcomes unconditionally and then decomposing these differences using available information on demographics and other observables. Section 3 also describes sorting patterns across occupations, industries, and firms. The last part of Section 3 details the role of motherhood in the wage gap over time. Section 4 concludes.

2 Data

The data in this paper are Danish administrative data primarily from IDA, which is a matched employer-employee longitudinal database containing demographic information on the Danish population (such as gender and age), labor market outcomes (such as employment, wages, and yearly earnings), and identifiers for both the establishment in which a worker is employed and also the firm (tax entity) in which a worker is employed. Both persons and establishments can be monitored from 1980 onwards, and firm id's can be linked to accounting information from 1995 onwards. Firms are connected to workers in the last week of November of every year.

Yearly earnings of a worker are available for all workers receiving positive labor income. Statistics Denmark also creates a measure of hourly wages based on hours worked as estimated from pension contributions. However, these wage measures are low-quality for workers with limited labor market attachment. We use only high quality wage observations which do not rely heavily on imputation from bracketed hours worked[2]. A notable pitfall of this data is that all full-time workers fall into the same hours bracket. We have de-trended earnings and wages according to the Danish 2012 consumer price index. Part-time employment is measured based on pension payments and is defined as working below 28 hours per week.

The register also include information on industry, occupation, and municipality of work as well as workplace and individual identifiers. Occupation is the ISCO08 after 1990 and a mea-

[2] tlonkval$<$ 50, which corresponds to workers working more than half-time.

sure of primary labor market attchment before 1991. The primary labor market attachment is constructed by Statistics Denmark and classified based on ILO recommendations. Industry is a five digit industry classification based on NACE rev. 2. Accumulated labor market experience is measured as the total number of registered working hours based on mandatory pension payments. We add background information on education, gender, and the birthdates of children in order to form our primary sample for analysis. The education data is based on a four digit educational classification including both duration and type of schooling. We focus on the labor market outcomes of men and women between 15 and 66 for our general descriptive statistics, and the restrict the sample to men and women between 25 and 60 for our more detailed analysis in order to avoid part-time work during secondary school and retirement.

3 Results

3.1 Unconditional Differences

In this section we show the unconditional differences between men and women in key labor market variables. Figure 1 plots the average earnings of women as a fraction of the average earnings of men from 1980-2011, as well as the average wages of women as a fraction of the average wages of men over the same period. The fifteen percentage point difference between the wage and earnings gap in 1980 has shrunk to a difference of less than five percentage points in 2010. This convergence between the wage and earnings gap is driven by an increase both in the proportion of women working, and also by an decrease in the proportion of women who are part time as we will show next.

Figure 2 below plots the fraction of the population between 15 and 66 years old making non-zero labor income over the course of the year. The sample excludes those in school. While the labor force participation of Danish men has been fairly stable over the period, women have increased their rate of employment from about 60% in 1980 to almost 70% before the recession.

Figure 3 plots the fraction of the population between 15 and 66 years old and working part time, again excluding those in school. Like labor force participation, there has been a huge convergence in the work hours of women compared to men. Convergence is not complete, however, since women are still about 4 percentage points more likely to be in part time work than men. In 1980, the difference was 30 percentage points.

Figure 4 plots the fraction of the population between 15 and 66 years old and working in the public sector, excluding those in school. There is a stable difference of about 25 percentage points in the fraction of women working in the public sector compared to men. The public sector includes healthcare, education, other government work and represents about 40% of Danish GDP. Women make up about 70% of the public sector in Denmark. Interestingly, the pay gap is larger in the private sector than in the public sector—restricting to private sector workers, the raw earnings and wage gaps are larger. Figure 5 plots average earnings of women as a fraction of the average earnings of men in the private sector (the private sector analogue to Figure 1).

The difference between the wages of men and women in Denmark are not concentrated in one particular portion of the wage distribution and are not driven by the highest-earning men. In fact, there is a fairly constant gap in the level of hourly wages, and a declining gap in percentage terms across wage quartiles. The 10th, 50th, and 90th percentile of male earnings, compared to the 10th, 50th, and 90th percentile of female earnings all show pay disparities, as plotted in Figure 6. The log difference in male and female wages at the 10th, 50th, and 90th percentiles, respectively is -.22, -.22, -.33 in 1980. By 2010 these figures are -.06, -.14, and -.28, as in Figure 7. All of these percentiles have converged, but the largest change occurs in the bottom decile of the distribution, and most of this convergence happened during the recession. In contrast, there is the smallest change (only 4 percentage points) in the relative wage of the top decile of women compared to the top decile of men, where the initial gap was also the largest.

The decline in the wage gap occurs both within and across cohorts. Figure 8 plots the wage gap in Denmark, by cohort birth year (plotting the cohort born every five years from 1930-1980) during their working life—25-60. As in Goldin [2014] which studies the US gender wage gap, the Danish wage gap rises over a women's working life, peaking around age 40. The same pattern holds for earnings, though more weakly, as in Figure 8.

Variation within the working life is dominated by variation across cohorts. The wage gap for 40 year olds born in 1940 is 35 percent. The wage gap for 40 year olds born five years later, in 1945, is 30 percent. The wage gap for 40 year olds born 10 years later, in 1950, is 25 percent. By the 1970 cohort, the gap is about 20 percent at age 40. There is less of difference in the wage gaps of different cohorts later in their working life. The 1930 cohort experienced a gap

of 25 percent at age 60, while the 1950 cohort experienced a gap of about 17 percent. Thus, differences experienced early in life seem to persist over time.

3.2 Conditional Differences

In this section we look at relative wages over time and how these patterns change when we condition on various observable characteristics. Figure 10 shows the coefficients on an indicator of whether a worker is female from a regression of log wages on the female indicator as well as a variety of controls. In particular, for every year from 1980-2010, we run the regression

$$\log(w_i) = \alpha + \beta 1\{Female\}_i + \mathbf{X}_i\gamma + \varepsilon_i$$

where w_i is the wage of worker i in a given year, $1\{Female\}_i$ is an indicator of whether the worker is female, and $\mathbf{X}_i$ is a vector of controls. Figure 10 plots β in every year 1980-2010 for five different regressions. In the first (baseline) regression, $\mathbf{X}_i$ includes age and education dummies, where education is a three digit indicator of not only years of completed schooling, but also type of schooling—for college degrees, broad school of study, such as social sciences, humanities, etc[3]. The second regression (orange line) adds a linear, quadratic, and cubic terms in experience. The third regression adds occupation fixed effects (3 digit ISCO codes). The fourth regression adds establishment fixed effects. The final regression, which decreases the wage gap to about 10 log points, replaces occupation and firm fixed effects with the interaction of occupation and firm fixed effects

The effect of detailed information on occupation is evident going from 1990 to 1991, when detailed occupation codes become available. Before 1991, occupation categories are limited to management, high skilled, white collar, and low skilled. More detailed occupation categories (3-digit ISCO categories) explain an additional 4 percentage points of the wage gap, which is quite substantial. However, the importance of occupation in explaining the wage gap has been declining since the early 1990s, while the relative importance of firm effects has been increasing over this period. This contrasts with Blau and Kahn [2016] who study the role of occupation in explaining the gender wage gap in the US using the PSID and conclude that differences in occupational choices between men and women have become relatively more important in

[3]these are 4 digit hffsp codes

explaining the gender wage gap between men and women.

To study the role of differences in observable characteristics like occupation more formally, we next provide a Oaxaca-Blinder decomposition of log wages in 1980, 1995, and 2010. The Oaxaca-Blinder decomposition quantifies the difference in the wage gap that is explained by differences in observables, vs. differences in coefficients by running separate wage regressions on male and female wages. The coefficients in Figure 10 are to some extent averages of any differences in returns. The Oaxaca-Blinder decomposition in Table 4 gives the log points difference in wages explained by differences in the average educational attainment, occupation, age, experience, and industry of men compared to women.[4] In general, we see that both differences industry, occupation, and experience explain a large part of the gender wage gap, whereas differences in education and age does not matter much. What remains of the gender wage gap in 2010 cannot easily be explained by age, occupation, industry, experience, or education differences between men and women. This contrasts with the 1990s and 1980s when about fifteen percentage points of the gap could be explained by differences in these variables.

3.3 Gender Segregation on Industry, Occupation, Education, and Firm

There is a great deal of sorting in the labor market. 35% of establishments are all-male in 1980, while an additional 23% of establishments are all-female. By 2010, these figures are little changed—34% of establishments are all-male and 20% of establishments are all-female. This sorting is evident at the industry and occupation level as well. Figure 11 plots the fractions of an industry which is female in 2010 against the fraction female in 1980. There has not been any great reduction in industry-level segregation over this period. There is also a great deal of segregation. In the construction industry, 1 in 10 workers is female, approximately the same fraction as in 1980. In the health and social work sector, women make up about 90% of the workforce currently, but were just over 80% of the workforce in 1980.

It is often argued, see e.g. Card et al. [2016], that a segregated labor market leads to so-called female or male occupations (or industries) and that the females occupations pays lower wages because women have less bargaining power. Figure 12 plots the ratio of average female wages to average male wages against the fraction of an industry which is female in both 1980 (red dots) and 2010 (blue dots). In both years, there is a little to no correlation between the

[4] This is analogous to Table 4 in Blau and Kahn [2016].

fraction of the industry that is female and the ratio of female to male wages. There is, however, a great deal of variation in the wage gap by industry, variation which has not collapsed since 1980. The standard deviation of women's relative wages by industry is 0.106 in 1980 and 0.102 in 2010. Thus, it does not seem to the case that women move into industries in which they can earn more relative to men.

We can make the same figures by occupation. Figure 13 plots the fraction female in a given occupation (3 digit ISCO codes) in 1995 vs. 2009[5]. The label attached to each point is the occupation's 3-digit ISCO code. Codes are available on the International Labor Office website, and are summarized Appendix Table 4. The color of each label represents the broad (1-digit) occupation category. Women have become a larger fraction of the professional labor force since 1995, and a smaller fraction of the services and sales workers labor force. In general, occupations which were between 20 and 50 percent female in 1995 had the greatest change in the share of the occupation which is female in 2010. Occupations which were heavily female in 1995 have become more gender neutral, and occupations which were heavily male have become only slightly more female. Figure 14 plots relative women's wages against the fraction female by occupation. There is no strong relationship between the relative wage of women compared to men and the fraction of the occupation which is female. The greatest difference between the wage gap from 1995 to 2009 occurs in occupations which are 10-25 percent female, where the wage gap has narrowed substantially. The lack of relationship between occupation-specific wage differentials and occupational sorting is not very consistent with differences in discrimination driving occupational sorting, but it is consistent with preferences driving occupational sorting, at least to the extent that discrimination would show up as a wage differential.

The story is quite different for education. Women have been getting more education, especially more master's degrees relative to men in Denmark. Figure 15 plots the fraction female in a given education level and specialization[6]. Colors indicate specialization (arts, humanities, social sciences, physical sciences, engineering, etc.) and symbols indicate the level of education completed in this specialty. Vocational training is not classified by specialization because those specializations do not align well with the other categories. The fact that most observa-

[5]detailed occupation categories are only available 1991 onwards and occupation codes are consistent through 2009. Before 1991, occpation is the primary labor market attachment constructed by Statistics Denmark and classified based on ILO recommendations with four broad employment catagories: blue collar jobs, white collar jobs, managerial jobs, and high-skill jobs requiring special education/training.

[6]This grouping is equivalent to the information in 4-digit education codes used in the regressions to follow

tions lie above the 45 degree line reflects relatively more women getting educated. However, this increasing education of women is not necessarily in the fields with the smallest wage gap. Figure 16 plots the relationship between the relative wage of women compared to men and the fraction female in a given education group (specialization interacted with level of education). The points are weighted by the popularity of the education group, and there is certainly less sorting in education than in occupation.

The rich administrative data available in Denmark also allows us to estimate the firm-level differences in wages for men compared to women. We begin by following methods described in Card et al. [2016] (henceforth CCK) to run a gender-specific worker-firm fixed effects decomposition of wages. We decompose wages separately for the years 1980-1989, 1990-1999, and 2000-2009. We focus on establishment level, rather than firm level sorting, since many women work in the public sector and we do not want eliminate those observations from our description of the general trends in Denmark.

We estimate an additive two-way fixed effects model as developed in Abowd et al. [1999]—and AKM model. As in CCK, all coefficients are allowed to vary by gender. More specifically, we estimate

$$w_{it} = \alpha_i + \phi^{G(i)}_{J(i,t)} + X'_{it}\beta^{G(i)} + r_{it} \tag{1}$$

where w_{it} is the log wage of worker i at date t, $J(i,t)$ is the id of the establishment employing worker i at date t, $G(i)$ indicates the gender of worker i, and X_{it} is a vector of controls which includes year dummies interacted with education dummies, and quadratic and cubic terms in age interacted with education dummies. Equation (1) is estimated separately for men and women. As mentioned above, we estimate three versions of this system of equations: one in the 80s, one in the 90s, and one in the 00s, giving a total of 6 regressions of the form 1.

We can decompose the average difference in establishment-effects for women compared to men into a sorting component and a bargaining component.[7] After estimating firm effects by gender from equation (1), we can decompose the average difference in firm effects into what

[7]Because establishment fixed effects are identified relative to some baseline, in order to compare establishment effects for women and men, we must jointly normalize the effects. As in CCK, we assume that

$$E\left[\phi^{G}_{J(i,t)} | \bar{S}^{0}_{J(i,t)} \leq \tau\right]$$

where $\bar{S}^{0}_{J(i,t)}$ is the employment-weighted average value added per worker at establishment J over time. Under this assumption, average establishment-effects for establishments with value added per worker below some threshold

women would be paid if they worked at the firms men work at (a sorting effect) and what women would be paid at their own firms if they were men (what CCK refer to as a bargaining effect):

$$E[\phi^M_{J(i,t)}|m] - E[\phi^F_{J(i,t)}|f] = \left\{E[\phi^M_{J(i,t)} - \phi^F_{J(i,t)}|m]\right\} + \left\{E[\phi^F_{J(i,t)}|m] - E[\phi^F_{J(i,t)}|f]\right\}$$

The first term in this equation is the bargaining effect and the second term is the sorting effect. Since the sorting term uses only the fixed effects from one regression and takes a difference, it is invariant to the normalization. However, the overall gap between male and female establishment effects is not. In this paper we are interested in whether sorting across establishments by gender has changed over time. Instead of limiting our data to firms with accounting records (private sector firms from 1995 on with a larger fraction men than the overall economy), we use all wage data with available establishment id. We do not give estimates of the bargaining effect, only the sorting effect $\left\{E[\phi^F_{J(i,t)}|m] - E[\phi^F_{J(i,t)}|f]\right\}$.

Table 2 gives our results on the role of sorting—the difference between $E(\hat{\phi}^F|f)$ and $E(\hat{\phi}^F|m)$—compared to the wage gap. We find a small role for establishment-level sorting in explaining the gender wage gap. Sorting explains only .007-.027 log points of the gap, depending on the decade. The role of sorting rises over time, however, so that establishment level sorting now explains more than 10 percent of the difference in log wages between men and women, while in the 80s it explained almost none of the difference in wages.

The rising role of establishments, when compared to the declining role of occupation and industry in explaining the gender wage gap in Denmark, suggests that despite getting more educated and moving into higher wage occupations relative to the 1980s, women increasingly work in lower-paying establishments. This observation could have a variety of explanations, from non-wage differences in compensation in these establishments to discrimination in hiring at high-wage establishments. Whatever the explanation, the role of sorting is smaller than the

are 0. We choose the threshold based τ using non-linear least squares estimation of the equation

$$\hat{\phi}^{G(i)}_{J(i,t)} = \pi^{G(i)}_0 + \pi^{G(i)}_1 \max\left\{0, \bar{S}^0_{J(i,t)} - \tau\right\} + \nu^{G(i)}_{J(i,t)}$$

The results of this estimation (using only firms with accounting data) are detailed in Appendix Table 4. After estimating τ and by-gender firm effects from equation (1), we normalize the fixed-effects to be on average 0 for firms with average value added per worker less than $\hat{\tau}$. However, in this subsample of firms with accounting data, the role for sorting is substantially smaller—only 1 log point. We instead focus on identifying the sorting effect only (which requires no normalization) for all establishments.

role of sorting found by CCK in Portuguese data. They estimate that sorting accounted for about 3.5 percentage points of the residual wage gap in Portugal between 2002 and 2009. We find that sorting accounts for closer to 2.5 percentage points of the (smaller) residual wage gap in Denmark.

Bagger et al. [2013] find increasing sorting of high wage workers into high wage firms from 1980 to 2006. The increasing sorting pattern holds for both men and women, but it is primarily driven by men. Thus, the difference could contribute to an increased gender wage gap.

Overall, our results suggest that sorting across industry, occupation, education-type, and establishment does not drive the wage gap. Women are becoming increasingly more educated, so much so that controlling for education actually increases the residual wage gap. While women do increasingly sort into lower-wage establishments than men, the magnitude of this sorting cannot explain a substantial portion of the wage gap. Occupational sorting, while quite dramatic, also does not explain a substantial portion of the wage gap, especially in recent years. However, the combined role of establishment-level sorting and occupation sorting is about the same between the 1980s and the 2000s. Together, these explain about 30% of the wage gap. We next briefly study one explanation which has been receiving considerable attention in the literature lately—the role of motherhood in explaining the gender wage gap.

3.4 Motherhood and the wage gap

The difference between the earnings and wages of mothers compared to non-mothers has also evolved. Table 4 gives the difference in log wages and log earnings of mothers relative to non-mothers in Denmark in 1980, 1995, and 2010, controlling for age in a linear regression with age dummies and an indicator for whether a woman has children. The sample is restricted to women between age 25 and 45. For the sample of men between 25 and 45, fathers earn 5-9% higher wages compared to non-fathers (conditioning only on age) in 2010. On the other hand, mothers earn 9-5% lower wages than women without children (conditional only on age). The difference in the motherhood penalty in wages has fallen over time, while the fatherhood premium is higher in 2010 than it was in 1980 or 1995. The decline in the wage penalty for mothers is smaller than the decline in the earnings penalty: in 1980, mothers earned almost 25% less than non-mothers, while in 2010, they earn only 3 percent less. It should be emphasized that this difference does not reflect differences between mothers and non-mothers in education,

industry, experience, and most importantly, ability. All of these omitted variables are likely correlated with the choice to have children and of course affect wages[8].

Kleven et al. [2015] provide a less aggregated measure of the cost of children in Denmark and describe how it has changed from 1980 to the present day. Their empirical strategy is to use an event-study framework to analyze the lifetime costs of children. The authors estimate earnings regressions for men and women that include a measure of distance from the birth of the first child (relative to the year before birth), as well as age and year dummies. The child-penalty t years after birth is the difference between the effect of children t years after birth for women compared to men as a fraction of average female earnings t years after birth. In addition to earnings as an outcome of interest, the authors also study wages, hours worked, and labor force participation. The authors find that gender inequality in earnings attributable to having children has increased from 18% in 1980 to 20% in 2013. The overall earnings penalty is 19.4% and this is in roughly equal parts attributable to a decline in labor force participation, a decline in hours worked, and a decline in wages.

4 Conclusion

This paper documents the changing nature of the gender pay gap in Denmark. We find that overall the earnings gap shrank by more than 10 percentage points, while the wage gap shrank much more modestly, by about 3 percentage points between 1980 and 2010. The more the fifteen percentage point difference between the wage and earnings gap in 1980 has shrunk to difference of less than five percentage points. This convergence between the unconditional wage and earnings gap is driven by an increase both in the proportion of women working, and also by a decrease in the proportion of women who are part time.

Despite convergence on these dimensions, women in Denmark are proportionally as likely to be in the public sector in Denmark as they were in 1980. In the public sector, the wage gap is smaller, but in general it is not the case that women work in occupations with smaller wage gaps. Overall, the role of occupation and industry sorting in explaining the wage gap in Denmark is very modest. This was not the case in 1980, when about 10 percentage points of the wage gap could be explained (jointly) by gender differences in occupation, education, and

[8]For example, if the cost of motherhood is increasing in potential wages, we would expect the highest-ability women to put off child-bearing and have fewer children, biasing the true effect of children down.

industry. Now, those factors can account for about 6 percentage points of the gap. Overall, a larger fraction of the gender wage gap cannot be explained by observables in 2010 compared with 1980. Establishment-level sorting cannot account for the remaining gap, explaining only about one percentage point of the wage gap.

In general we find that demographics along with heterogeneity in job choice explain about half of the wage gap. The difference in wages of women compared to men is about ten log points in 2010, even when restricting to variation within firm-occupation. This difference in wages emerges around the time that women have children. Recent work on the gender wage gap in Denmark has highlighted the increasing role of motherhood in explaining (or, at least, in coinciding with) wage disparities between men and women. It seems that choices on this dimension within job, rather than on the potentially related dimension of occupation/industry sorting are responsible for an increasing fraction of the wage gap in Denmark.

Understanding the source of changes in wage gap decompositions is important for understanding the role and nature of discrimination in the labor market. We find notably different results in Denmark relative to the US—a declining role for occupational sorting in explaining wage differences and in general little change in the residual wage gap since the 80s. This is not the only difference between the two labor markets, of course (see Blau and Kahn [2013], Claudia Olivetti and Barbara Petrongolo [2008]), but certainly highlights the considerable heterogeneity in the evolution of the wage gap across countries.

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Figures

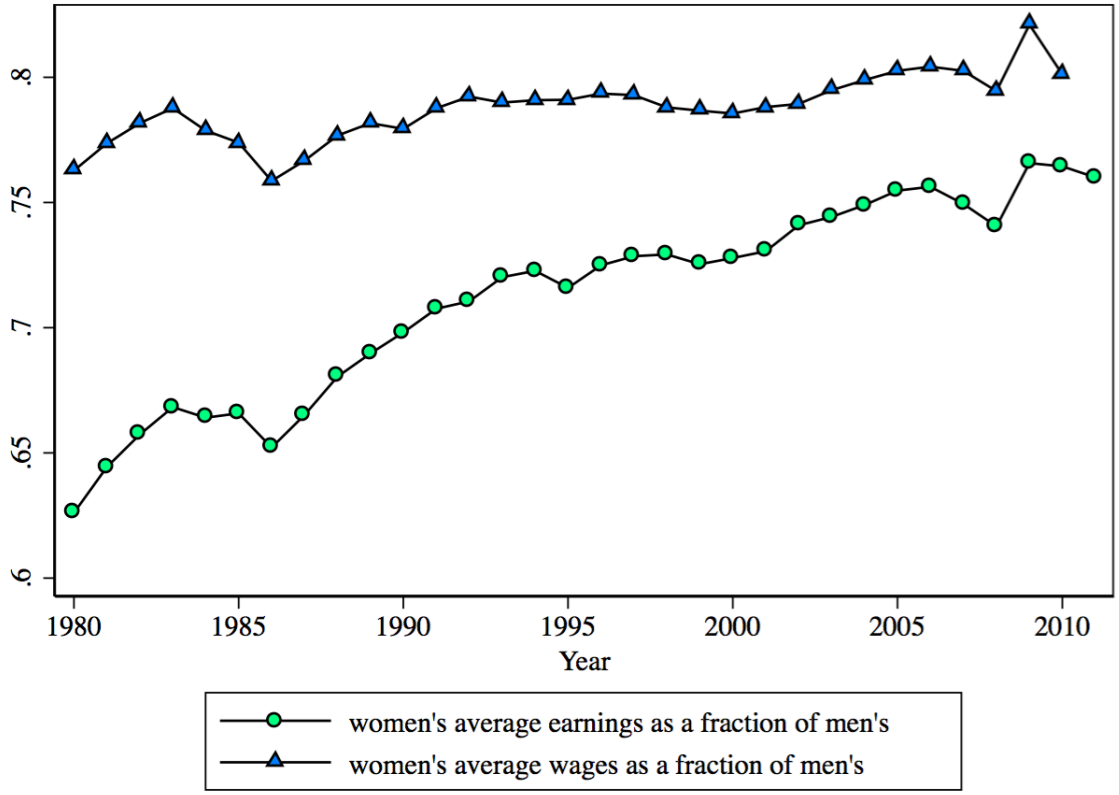

Figure 1: Plots the raw wage and earnings gap over time.

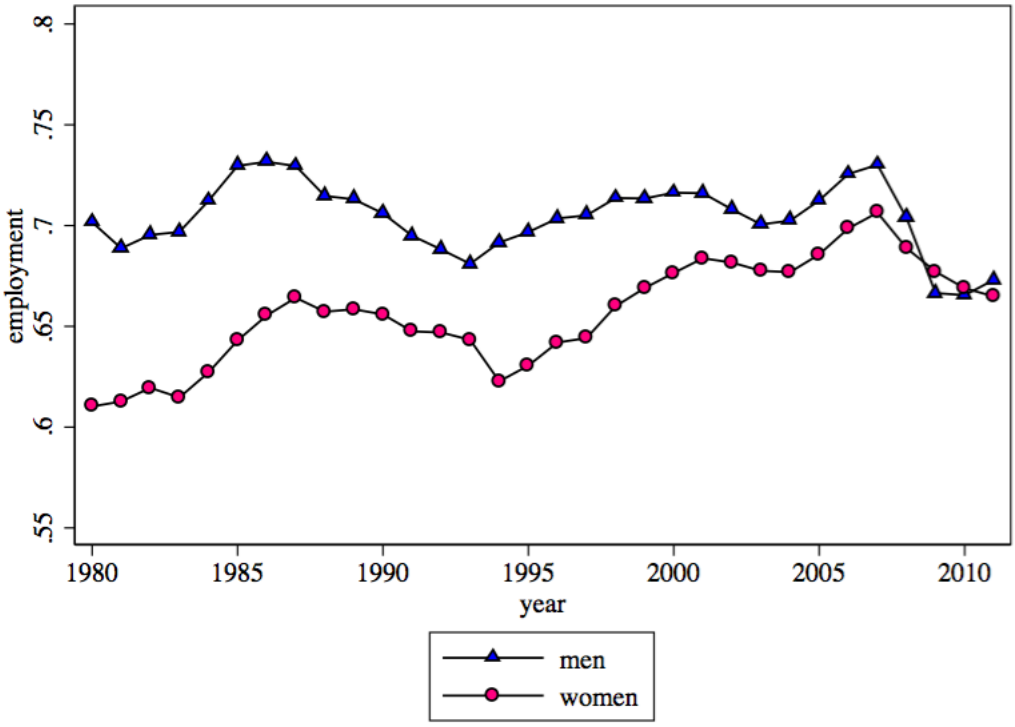

Figure 2: Plots the fraction of the population between 15 and 66 years old who is not in school and who is making non-zero labor income over the course of the year.

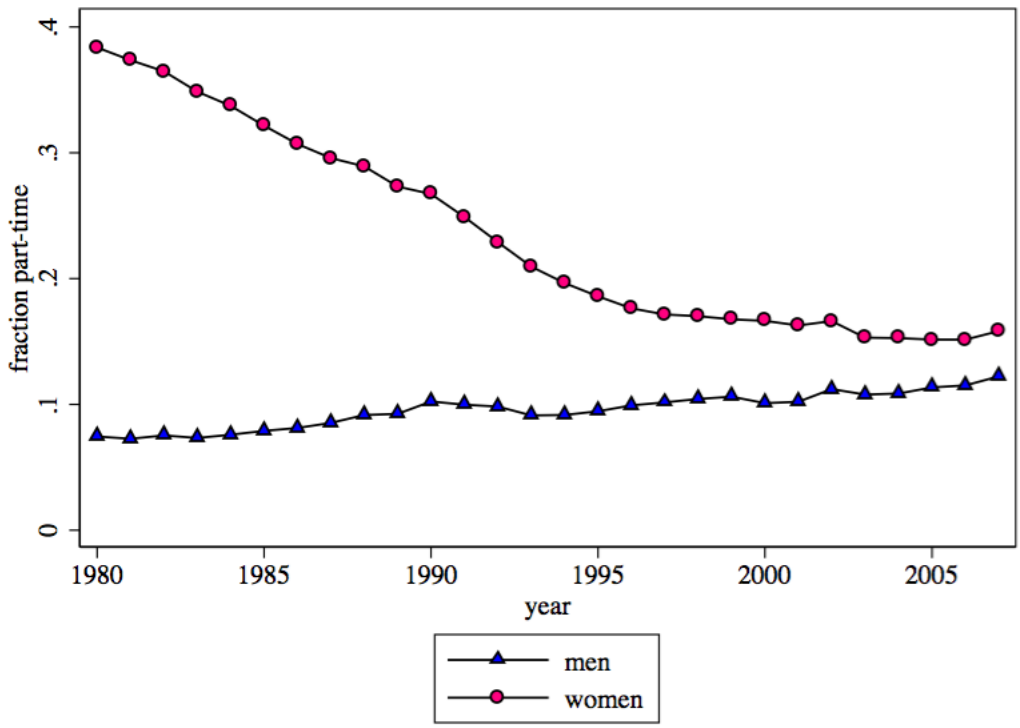

Figure 3: Plots the fraction of men and women in less than full time occupations over time.

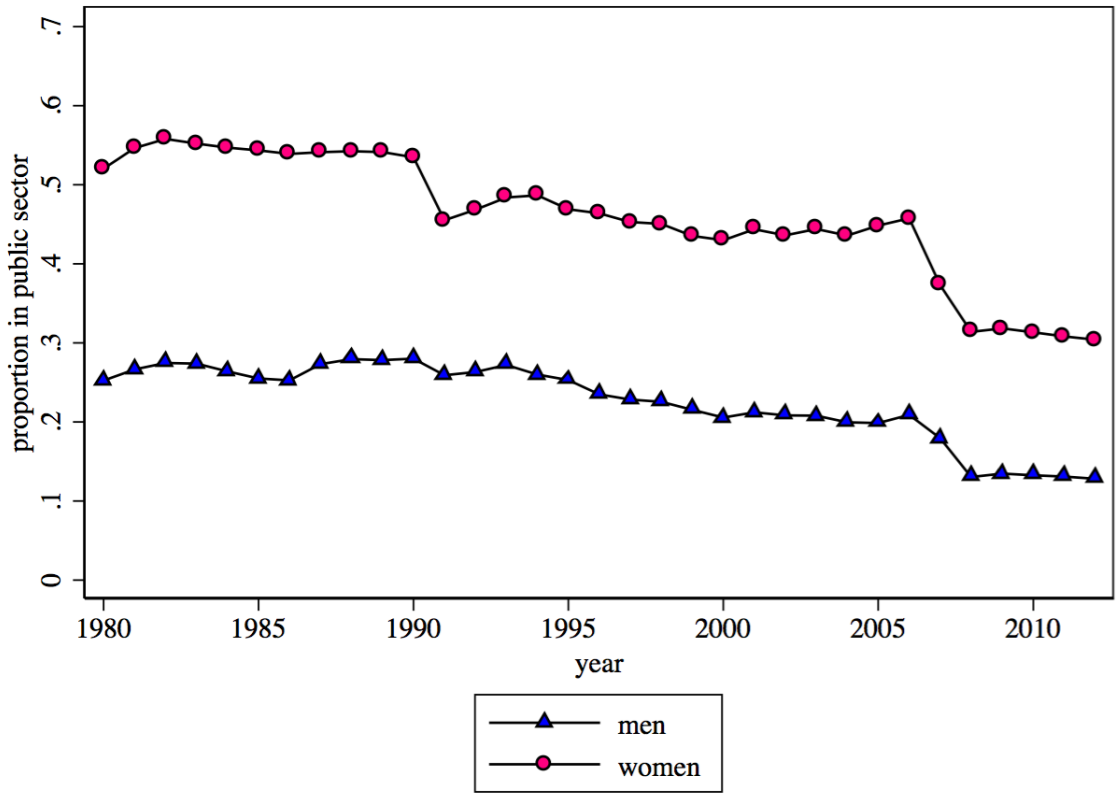

Figure 4: Plots the fraction of men and women in the public sector over time.

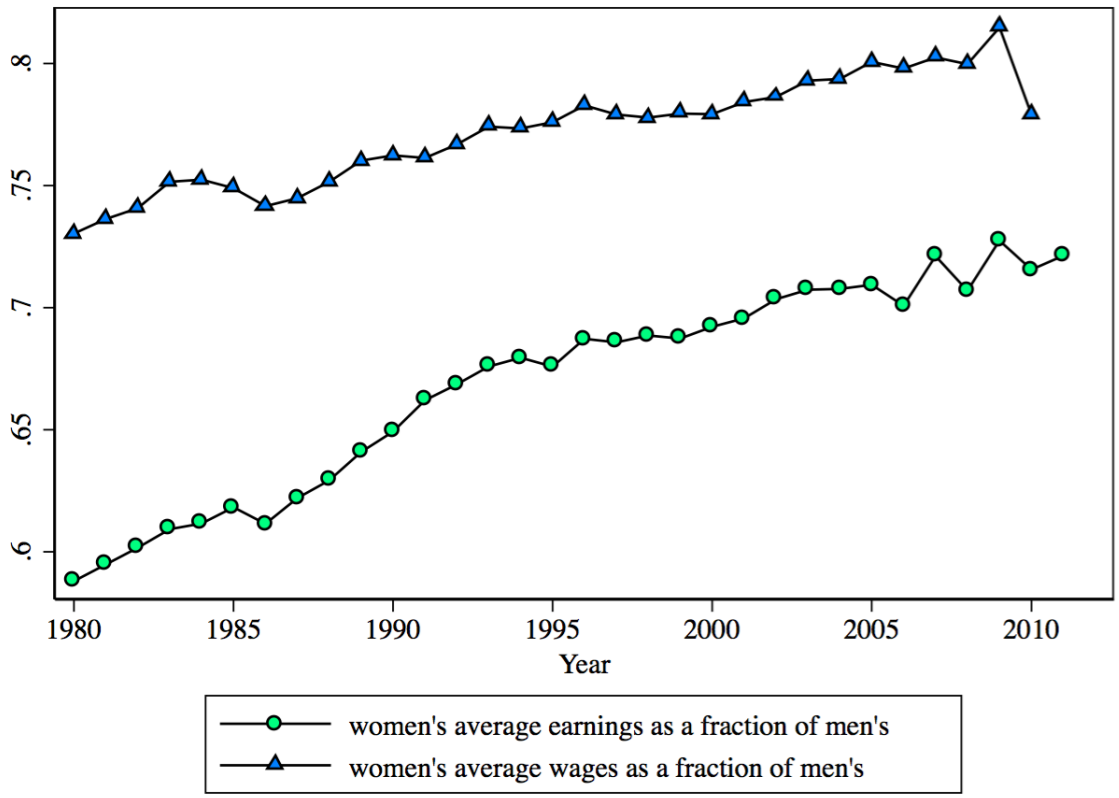

Figure 5: Plots the raw wage and earnings gap over time for workers working in the private sector only.

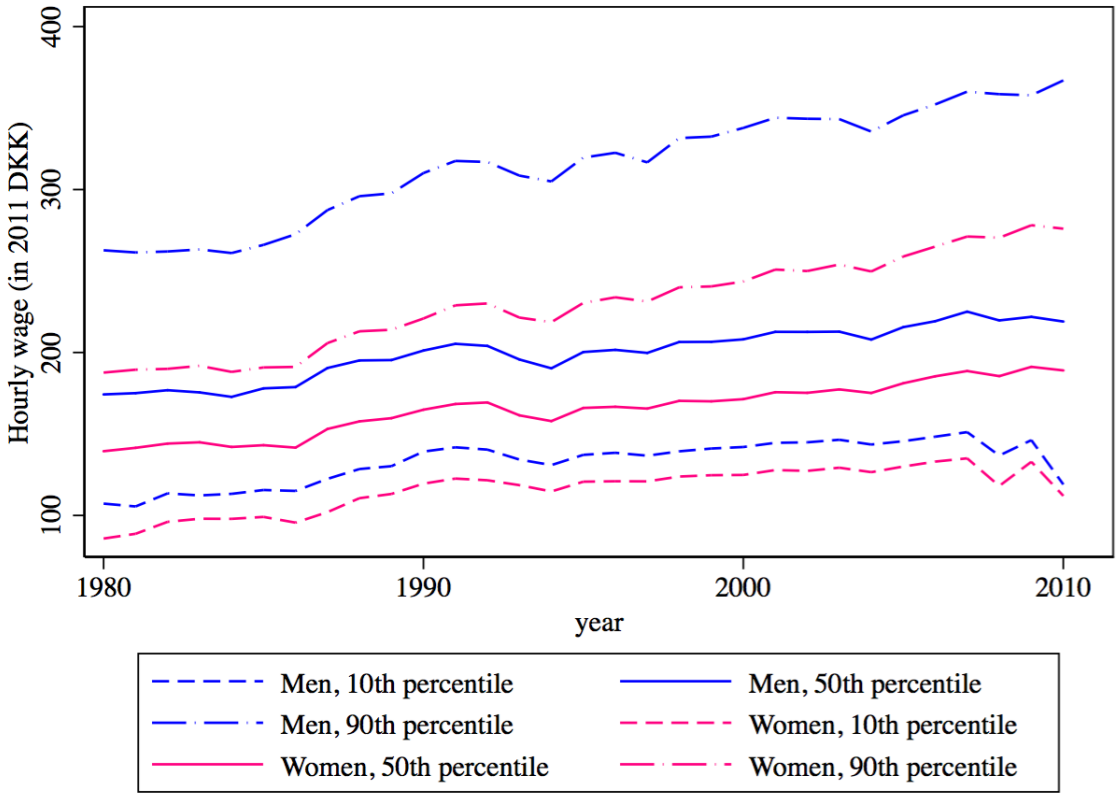

Figure 6: Plots the 10th, 50th, and 90th percentile of wages for men and women over time.

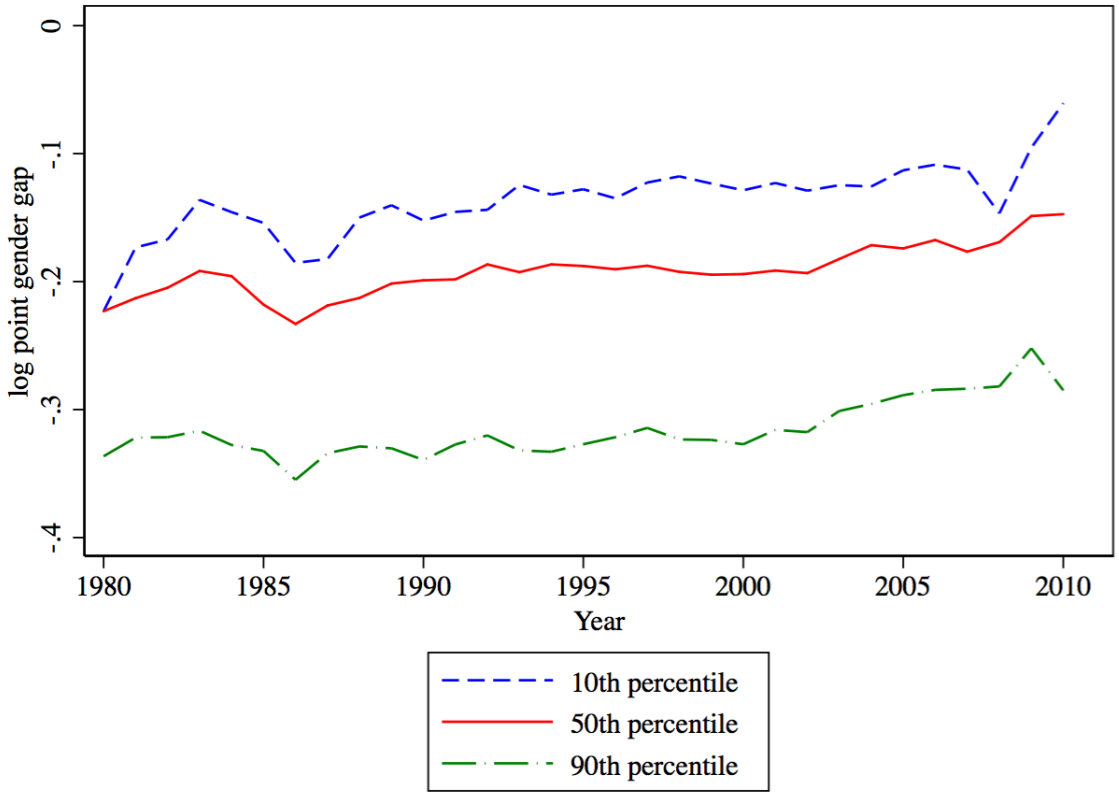

Figure 7: Plots the log difference in wages at the 10th, 50th, and 90th percentile of the male and female wage distributions over time.

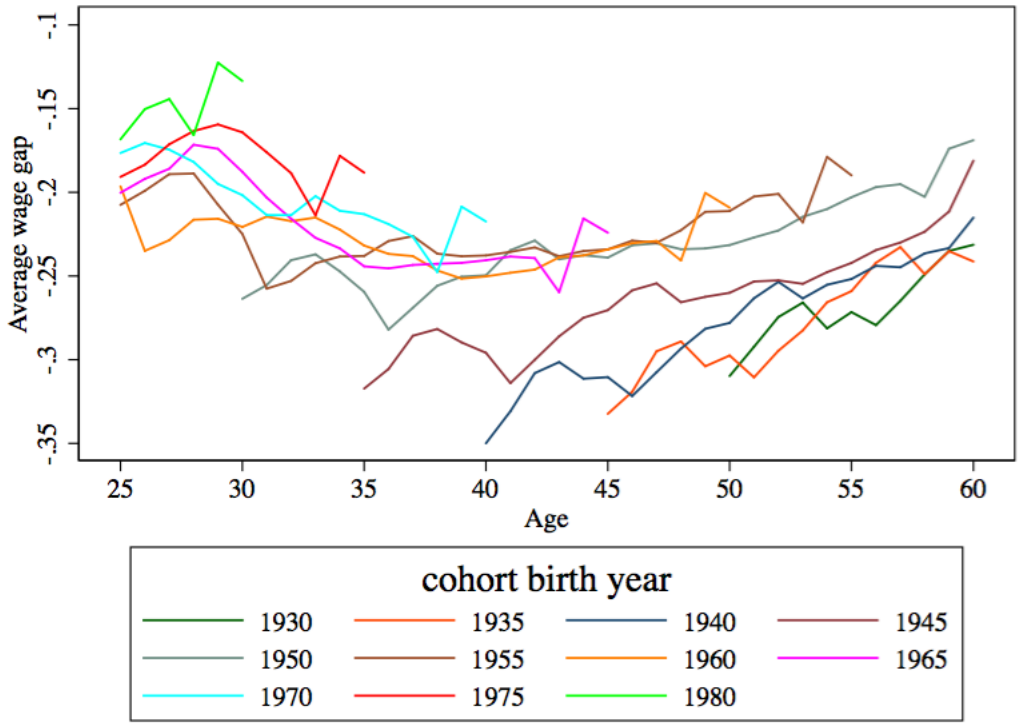

Figure 8: Plots the raw wage gap in Denmark, by cohort over their working life (25-60).

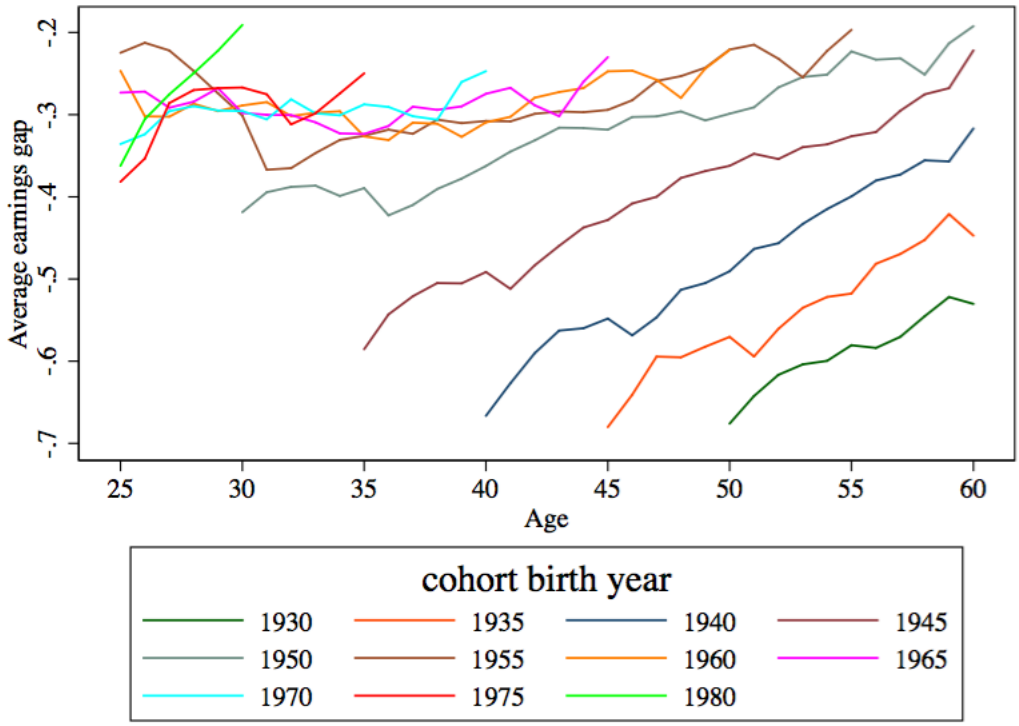

Figure 9: Plots the raw earnings gap in Denmark, by cohort over their working life (25-60).

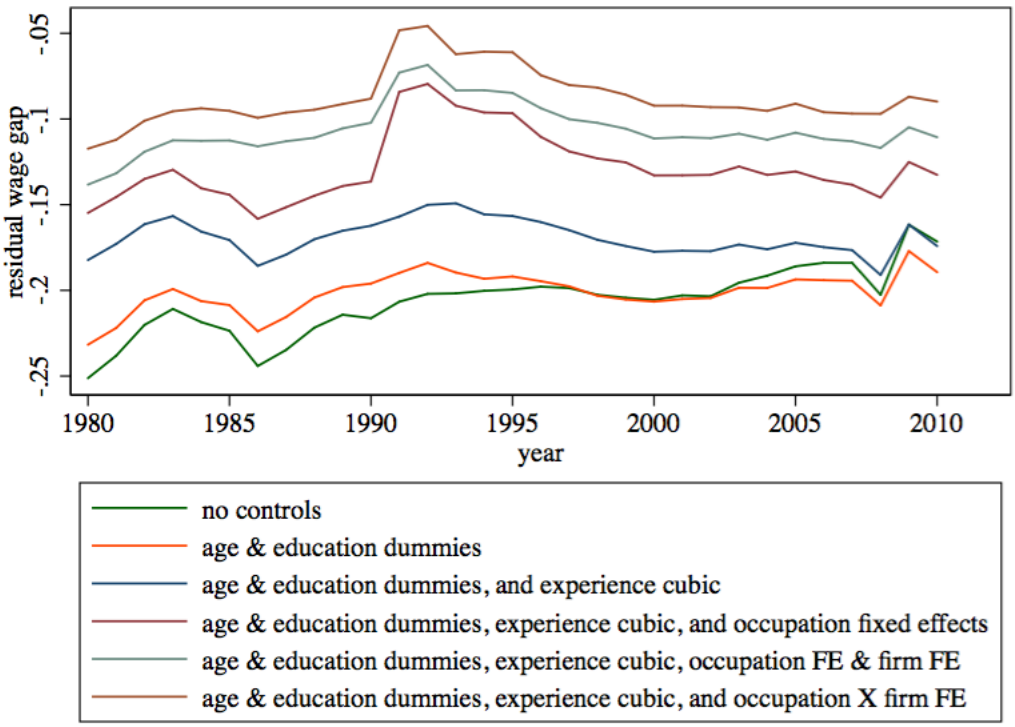

Figure 10: Plots the residual wage gap in Denmark under a variety of specifications, as described in the legend. The residual wage gap is the coefficient on an indicator of whether a worker is female, controlling also for the variables listed in the legend. The outcome variable is log wages.

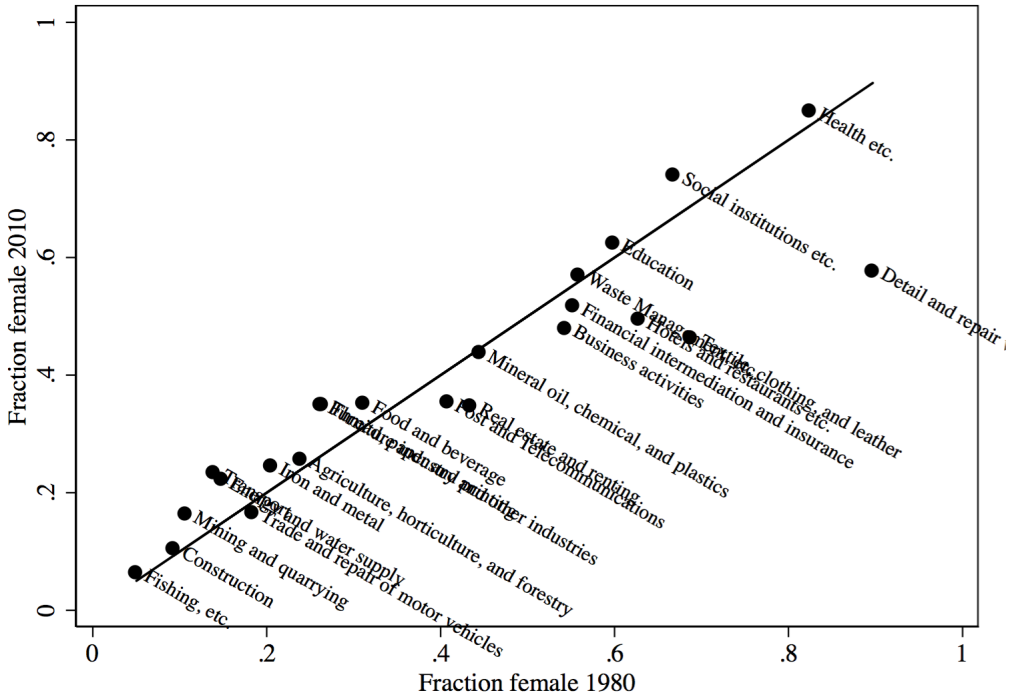

Figure 11: Proportion of women by industry, 1980 vs. 2010

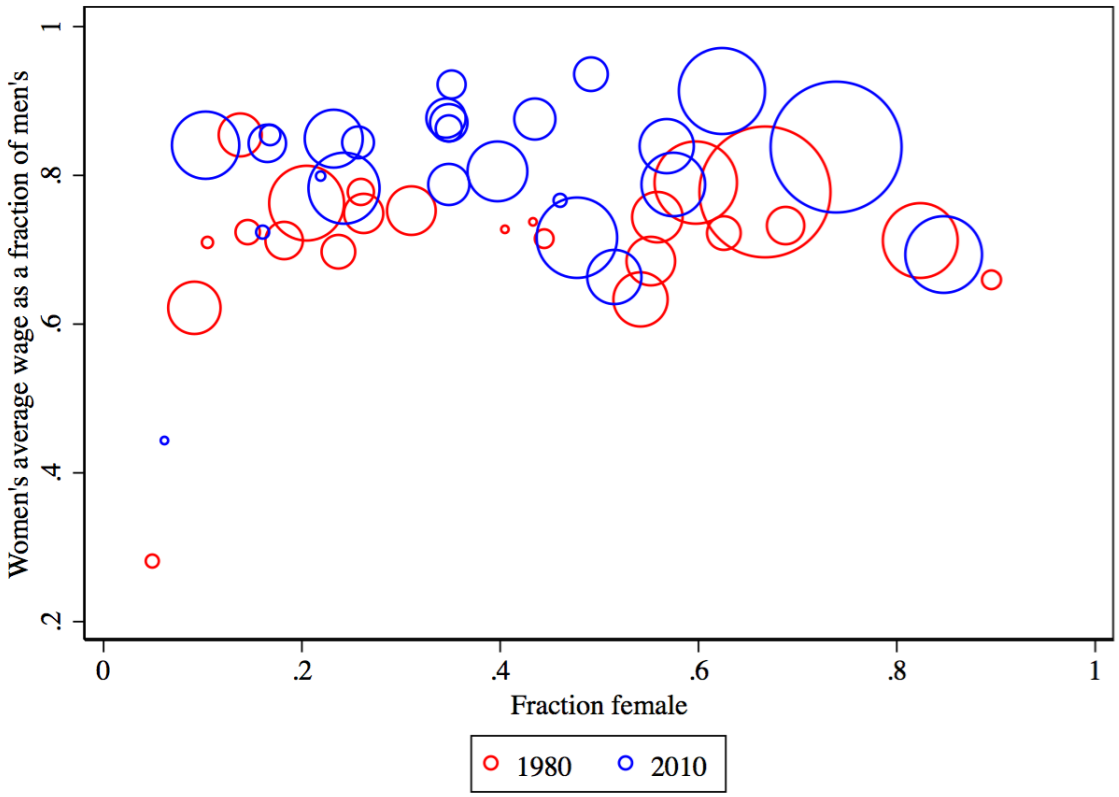

Figure 12: Women's wages as a fraction of men's vs. the proportion of women by industry, 1980 and 2010

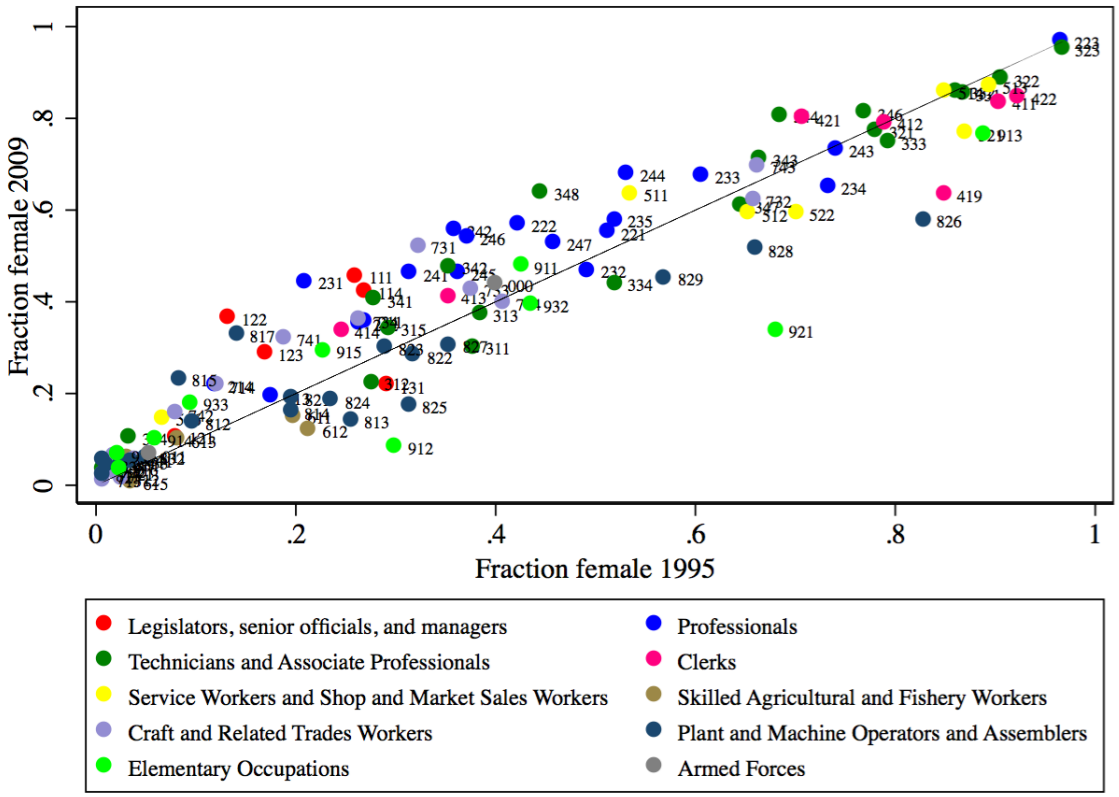

Figure 13: Proportion of women by occupation, 1995 vs. 2009. Labels refer to 3 digit ISCO-88 occupation codes. The occupations are groups into 1-digit ISCO-88 groups according to the legend above.

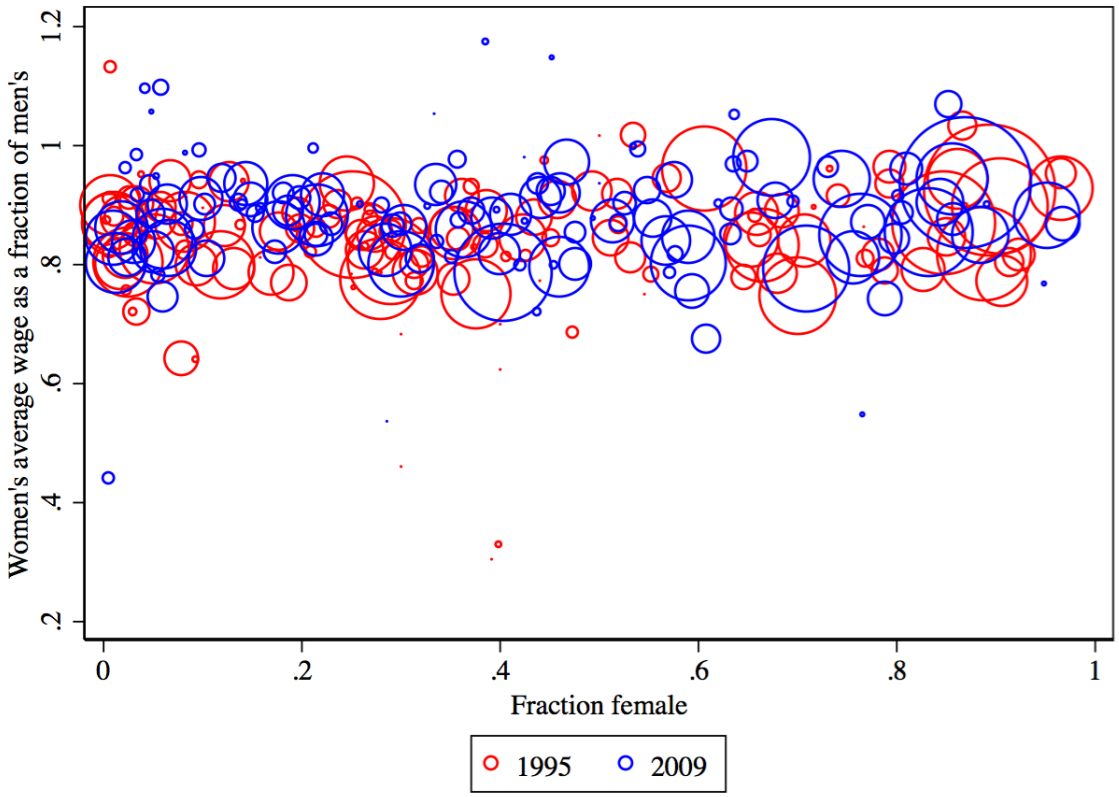

Figure 14: Women's wages as a fraction of men's vs. the proportion of women by occupation, 1995 and 2010

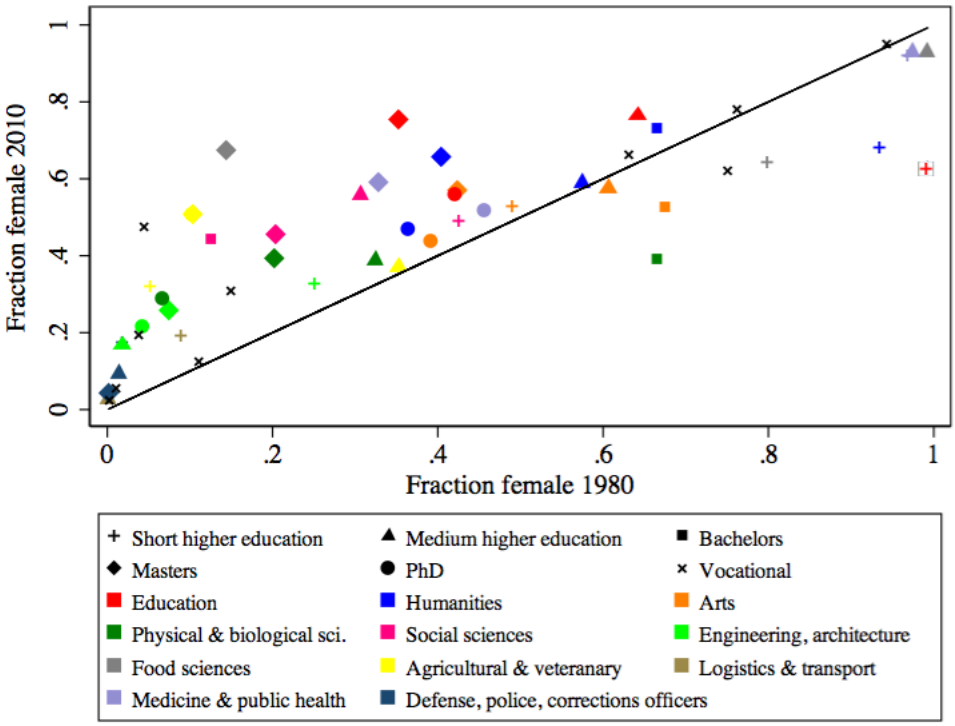

Figure 15: Proportion of women by education grouping (defined as specialization interacted with level of education), 1980 vs. 2010. Education of less than vocational training is omitted from this graph.

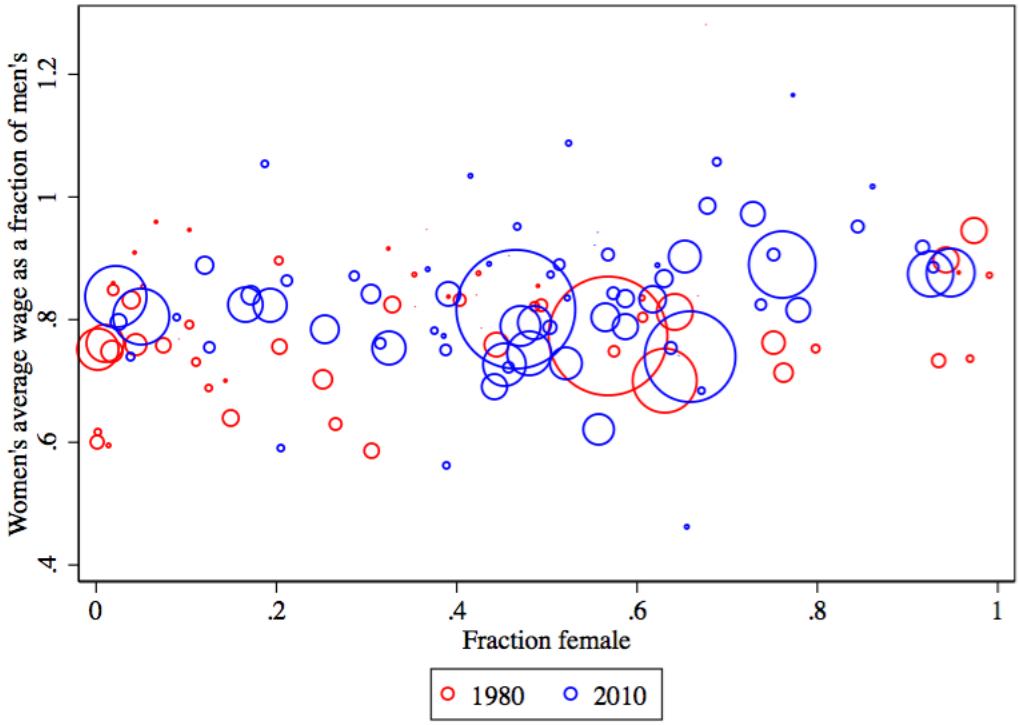

Figure 16: Women's wages as a fraction of men's vs. the proportion of women by education grouping (defined as specialization interacted with level of education), 1980 and 2010

Tables

Table 1: Decomposition of the Gender Wage Gap: 1980, 1995, and 2010

Sample	All workers			Private Sector only		
Year	1980	1995	2010	1980	1995	2010
Male $\log(w_i)$	5.246	5.376	5.484	5.257	5.398	5.495
	(.0003)	(.0004)	(.0004)	(.0004)	(.0004)	(.0005)
Female $\log(w_i)$	4.948	5.150	5.293	4.917	5.159	5.301
	(.0004)	(.0003)	(.0003)	(.0006)	(.0005)	(.0006)
Difference	.2981	.2264	.1903	.3405	.2391	.1947
	(.0005)	(.0004)	(.0005)	(.0008)	(.0006)	(.0008)
Total explained	.1547	.1266	.0635	.1467	.0957	.0232
	(.0008)	(.0008)	(.0008)	(.0009)	(.0011)	(.0010)
experience	.04857	.0274	.0114	.0416	.0292	.0110
	(.0004)	(.0002)	(.0002)	(.0005)	(.0003)	(.0002)
industry	.0307	.0413	.0312	.0136	.0128	-.0050
	(.0003)	(.0003)	(.0004)	(.0003)	(.0003)	(.0003)
education	.0194	.0144	-.0096	.0159	.0157	-.0023
	(.0007)	(.0007)	(.0008)	(.0007)	(.0008)	(.0007)
occupation	.0590	.0447	.0310	.0772	.0398	.0208
	(.0003)	(.0009)	(.0008)	(.0006)	(.0010)	(.0008)
age	-.0030	-.0012	-.0004	-.0016	-.0018	-.0011
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Total unexplained	.1434	.0998	.1268	.1939	.1434	.1715
	(.0009)	(.0009)	(.0008)	(.0011)	(.0011)	(.0010)
N^m	795668	905808	893812	573725	689874	672097
N^f	576039	767944	891729	246980	398068	379621

Sample includes all 25-60 year olds working at least half time. Experience captures the total the difference between male and female experience, experience squared, and experience cubed evaluated at the male log wage coefficients. Industry is the difference in 2 digit industry code indicators evaluated at the male log wage coefficients. See Figure 11 for a list of industries. Education is the difference in 4 digit educational attainment indicators (which includes both years of schooling and type of schooling) evaluated at the male log wage coefficients. In 1995 and 2010, occupation is the difference in 3 digit ISCO indicators evaluated at the male log wage coefficients. In 1980, occupation catagories are blue collar, white collar, high-skilled, and management. Finally, Age is the difference in age indicators evaluated at the male log wage coefficients.

Table 2: Firm Effects and the Gender Pay Gap

	1980-1989			
	Sorting		Log wages	
	$\hat{\phi}^F \mid f$	$\hat{\phi}^F \mid m$	$\log(w^m)$	$\log(w^f)$
Average effects	0.1096	0.1024	5.193	4.963
Difference $(f - m)$		-0.0071		-0.2300
	1990-1999			
	Sorting		Log wages	
	$\hat{\phi}^F \mid f$	$\hat{\phi}^F \mid m$	$\log(w^m)$	$\log(w^f)$
Average effects	-0.2772	-0.3001	5.311	5.114
Difference $(f - m)$		-0.0230		-0.1977
	2000-2009			
	Sorting		Log wages	
	$\hat{\phi}^F \mid f$	$\hat{\phi}^F \mid m$	$\log(w^m)$	$\log(w^f)$
Average effects	0.0706	0.0441	5.386	5.201
Difference $(f - m)$		-0.0266		-0.1852

Note:

Table 3: The motherhood penalty and fatherhood premium over time

Year	1980	1995	2010	1980	1995	2010
Sample	Women	Women	Women	Men	Men	Men
	$\log(\text{earnings}) = \alpha + \beta \mathbf{1}\{\text{Has Children}\} + D_{Age,i} + \varepsilon_i$					
Has Children	-0.2475***	-0.1434***	-0.0321***	0.1726***	0.1473***	0.2038***
	(0.0023)	(0.0021)	(0.0020)	(0.0016)	(0.0021)	(0.0019)
N	531559	558750	565068	591701	626829	568056
	$\log(\text{wages}) = \alpha + \beta \mathbf{1}\{\text{Has Children}\} + D_{Age,i} + \varepsilon_i$					
Has Children	-0.0911***	-0.0693***	-0.0461***	0.0687***	0.0533***	0.0898***
	(0.0012)	(0.0009)	(0.0011)	(0.0009)	(0.0009)	(0.0012)
N	423588	497792	512169	548305	581058	521823

Appendix

Table 4: Estimation of τ

Firm-effects intercept for males π_0^m	.079921
	.0002366
Firm-effects intercept for females π_0^f	-.023922
	.0002297
Firm-effects vs. surplus slope for males π_1^m	.0981743
	.000144
Firm-effects vs. surplus slope for females π_1^f	.0865092
	.0001941
Zero-surplus threshold τ	12.48289
	.0025088
N	9680681

Correlation between firm fixed effects and $\bar{S}_J^o$ is 0.244. The fraction of observations with $\bar{S}_J^o$ less than $\hat{\tau}$ is 0.049 in the female-only decomposition and 0.0357 in the male-only decomposition. However, the fraction of firms with $\hat{\phi}_J$ less than 0 when we use the normalization is .228 and .122, respectively.

Table 5: Decomposition of the Gender Wage Gap: 1980, 1995, and 2010, restricted to high-quality occupation data

Year	1980	1995	2010
Male $\log(w_i)$	5.246	5.388	5.525
	(.0003)	(.0004)	(.0005)
Female $\log(w_i)$	4.948	5.153	5.324
	(.0004)	(.0003)	(.0004)
Difference	.2981	.2342	.2008
	(.0005)	(.0006)	(.0006)
Total explained	.1547	.1438	.0736
	(.0008)	(.0008)	(.0009)
experience	.04857	.0227	.0073
	(.0004)	(.0003)	(.0001)
industry	.0307	.0358	.0232
	(.0003)	(.0004)	(.0004)
education	.0194	.0236	.0023
	(.0007)	(.0008)	(.0008)
occupation	.0590	.0629	.0419
	(.0003)	(.0010)	(.0008)
age	-.0030	-.0013	-.0011
	(.0001)	(.0001)	(.0001)
Total unexplained	.1434	.0905	.1272
	(.0009)	(.0009)	(.0009)
N^m	795668	543800	597648
N^f	576039	585114	567967

Sample includes all 25-60 year olds working at least half time on whom occupation classification is high-quality. Experience captures the total the difference between male and female experience, experience squared, and experience cubed evaluated at the male log wage coefficients. Industry is the difference in 2 digit industry code indicators evaluated at the male log wage coefficients. See Figure 11 for a list of industries. Education is the difference in 4 digit educational attainment indicators (which includes both years of schooling and type of schooling) evaluated at the male log wage coefficients. Occupation is the difference in 3 digit ISCO indicators evaluated at the male log wage coefficients. Finally, Age is the difference in age indicators evaluated at the male log wage coefficients.

Table 6: ISCO-88 Occupation Codes

Code	Definition	Code	Definition
111	Legislators	515	Astrologers, fortune-tellers and related workers
112	Senior government officials	516	Protective services workers
113	Traditional chiefs and heads of villages	521	Fashion and other models
114	Senior officials of special-interest organizations	522	Shop salespersons and demonstrators
121	Directors and chief executives	523	Stall and market salespersons
122	Production and operations department managers	611	Market gardeners and crop growers
123	Other department managers	612	Market-oriented animal producers and related workers
131	General managers	613	Market-oriented crop and animal producers
211	Physicists, chemists and related professionals	614	Forestry and related workers
212	Mathematicians, statisticians and related professionals	615	Fishery workers, hunters and trappers
213	Computing professionals	621	Subsistence agricultural and fishery workers
214	Architects, engineers and related professionals	711	Miners, shotfirers, stone cutters and carvers
221	Life science professionals	712	Building frame and related trades workers
222	Health professionals (except nursing)	713	Building finishers and related trades workers
223	Nursing and midwifery professionals	714	Painters, building structure cleaners and related trades workers
231	College, university and higher education teaching professionals	721	Metal moulders, welders, sheet-metal workers, etc.
232	Secondary education teaching professionals	722	Blacksmiths, tool-makers and related trades workers
233	Primary and pre-primary education teaching professionals	723	Machinery mechanics and fitters
234	Special education teaching professionals	724	Electrical and electronic equipment mechanics and fitters
235	Other teaching professionals	731	Precision workers in metal and related materials
241	Business professionals	732	Potters, glass-makers and related trades workers
242	Legal professionals	733	Handicraft workers in wood, textile, leather and related material
243	Archivists, librarians and related information professionals	734	Printing and related trades workers
244	Social science and related professionals	741	Food processing and related trades workers
245	Writers and creative or performing artists	742	Wood treaters, cabinet-makers and related trades workers
246	Religious professionals	743	Textile, garment and related trades workers
311	Physical and engineering science technicians	744	Pelt, leather and shoemaking trades workers
312	Computer associate professionals	811	Mining and mineral-processing-plant operators
313	Optical and electronic equipment operators	812	Metal-processing-plant operators
314	Ship and aircraft controllers and technicians	813	Glass, ceramics and related plant-operators
315	Safety and quality inspectors	814	Wood-processing-and papermaking-plant operators
321	Life science technicians and related associate professionals	815	Chemical-processing-plant operators
322	Modern health associate professionals (except nursing)	816	Power-production and related plant operators
323	Nursing and midwifery associate professionals	817	Automated-assembly-line and industrial-robot operators
324	Traditional medicine practitioners and faith healers	821	Metal-and mineral-products machine operators
331	Primary education teaching associate professionals	822	Chemical-products machine operators
332	Pre-primary education teaching associate professionals	823	Rubber- and plastic-products machine operators
333	Special education teaching associate professionals	824	Wood-products machine operators
334	Other teaching associate professionals	825	Printing-, binding-and paper-products machine operators
341	Finance and sales associate professionals	826	Textile-, fur-and leather-products machine operators
342	Business services agents and trade brokers	827	Food and related products machine operators
343	Administrative associate professionals	828	Assemblers
344	Customs, tax and related government associate professionals	829	Other machine operators and assemblers
345	Police inspectors and detectives	831	Locomotive engine drivers and related workers
346	Social work associate professionals	832	Motor vehicle drivers
347	Artistic, entertainment and sports associate professionals	833	Agricultural and other mobile plant operators
348	Religious associate professionals	834	Ships? deck crews and related workers
411	Secretaries and keyboard-operating clerks	911	Street vendors and related workers
412	Numerical clerks	912	Shoe cleaning and other street services elementary occupations
413	Material-recording and transport clerks	913	Domestic and related helpers, cleaners and launderers
414	Library, mail and related clerks	914	Building caretakers, window and related cleaners
419	Other office clerks	915	Messengers, porters, doorkeepers and related workers
421	Cashiers, tellers and related clerks	916	Garbage collectors and related labourers
422	Client information clerks	921	Agricultural, fishery and related labourers
511	Travel attendants and related workers	931	Mining and construction labourers
512	Housekeeping and restaurant services workers	932	Manufacturing labourers
513	Personal care and related workers	933	Transport labourers and freight handlers
514	Other personal service workers		

International Standard Classification of Occupations (ISCO-88). Source: http://laborsta.ilo.org/applv8/data/isco88e.html