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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 increases in hours worked by women as well as a decline in the gender wage gap. The data show a great deal of segregation across education tracks, occupations, and even workplaces, but this segregation has declined since 1980. These changes in segregation have been accompanied by a reduction in the role of observables in explaining the gender wage gap. The residual gender wage gap has been constant since 1980. The hours gap is not affected by changes in segregation at the occupation and education level: differences in these characteristics for women relative to men do not contribute to the hours gap in 2010 and they did not in 1980. However, a firm-worker fixed effects analysis suggests that 30 percent of the gender hours gap can be explained by the sorting of women into lower-hours workplaces. The hours gap is driven by mothers, the group for whom differences in employer, occupation, education, and experience also imply large differences in wages. The combined effect of hours and wages is a more than 20 percent gender earnings gap among well-attached (halftime-plus) workers between 25 and 60 years old, 10 percent of which cannot be explained by differences in hours, or in the readily observable characteristics of these workers.

1. Introduction

Despite advances in labor force participation, educational attainment, technology, and changes in institutions (child care, maternity leave pay, etc.), a gender earnings gap of around 20 percent persists in Denmark. This paper presents a broad overview of women's labor market experience over a more than 30-year period. We begin by showing that there have been substantial changes in gender segregation in higher education over the past 30 years, and smaller changes in segregation at the workplace and occupation level. In 1980, 56 percent of all education tracks had one gender composing 75 percent or more of degree holders. In 2010, this figure has fallen by almost half. These changes in segregation have been accompanied by a reduction in the role of observables in explaining the gender wage gap. While differences in worker characteristics (experience, education, occupation, and industry) explained more than half of the 30-log point gender wage gap in 1980, differences in these characteristics explain only about one third of the twenty log-point gender wage gap in 2010. The residual gender wage gap has hardly changed since the 1980s.

What has changed substantially is relative hours worked: the hours-gap was about thirteen percent in 1980 and is now less than two percent among workers who work at least half-time. However, while there is little difference in the hours worked of fathers and non-fathers, mothers work substantially less than non-mothers and the difference has not changed since 1980. Our paper adds to the literature by understanding how the difference in hours between men and women is influenced by differences in the establishments where they work and differences in their education and occupation choices.

While establishment level sorting explains about 15 percent of the wage gap in the 2000s, it explains 30 percent of the hours-gap in the 2000s. Establishment-level sorting by women into "low-hours" workplaces plays about the same role in explaining the hours gap in the 2000s as it did in the 1980s. We find that differences in education and occupation choices do not contribute to gender differences in hours worked. Overall, we conclude that the decrease in gender segregation in the labor market has narrowed the wage gap over the past thirty years but has done little to affect the hours gap. Combining these results, the earnings gap has declined substantially and is less and less explained by education, occupation, and establishment differences between men and women.

Comparing our wage results to the case of the US studied by Blau and Kahn (2016) who also perform a Blinder-Oaxaca decomposition of wages over time, we find a decreasing role of occupation in explaining the wage gap while they find an increasing role of occupation. In Denmark, differences in occupational choice explain only two log points of the gender wage gap in 2010. In 1980, the effect of occupation on the

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wage gap in the US and Denmark was similar, contributing slightly more than 5 log points to the gender wage gap in both countries.

Matched employer-employee data allow us to identify the plant where a worker is employed. Unlike the case of occupation, we do not find a decreasing role for establishment-level sorting over time using a Blinder-Oaxaca decomposition. Applying the methods developed in Card et al. (2016)— gender-specific AKM decomposition of wages—we find that firm-level sorting can account for about 15 percent (3.3 log points) of the gender wage gap in 2010, which is more than the 10 percent role establishment sorting played in 1980. Our results on the role of workplaces are similar to what is found in Card et al. (2016) using Portuguese data. Our results on the importance of segregation overall are broadly similar to those of Bayard et al. (2003) who found that segregation explained about half of the gender wage gap using the 1990 long-form US census.

We next turn to understanding the importance of segregation at the establishment, occupation and education level on hours differences between men and women. We apply the same by-gender decomposition to hours worked and find a larger relative role for establishment effects. This suggests that women work in establishments which can be characterized by fewer hours worked by any particular individual. Differences in education, occupation, and industry, however, do not play an important role in the observed gender differences in hours worked.

Our extension of the establishment-level sorting studied in Card et al (2016), applied to hours, is illuminating because it suggests that women may be sorting into not only lower-pay workplaces, but to an even greater extent into workplaces which offer fewer hours to all employees. In light of a growing literature documenting the importance of gender differences in preferences concerning hours worked (Goldin, 2014; Hotz et al., 2017; Mas and Pallais, 2017; Wasserman, 2017; Wiswall and Zafar, 2018), we may view lower average hours at a firm as a benefit firms are able to offer to interested employees. This compensating differential complicates the analysis of sorting by gender at the firm level: low wage firms may not be low utility firms.[1]

Though the hours-gap has declined overall, it has actually increased for mothers compared to fathers over our sample period from 1980 to 2010. Mothers both work fewer hours than fathers and sort into different firms and occupations than fathers. For non-parents, occupation, firm, and education choices explain none of the wage gap in 2010, but this was not the case in 1980.

The prominent role of motherhood in understanding firm and occupation choices of women has been explored in past work. 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. (Forthcoming) 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." We show that conditional on age, men who have had kids have higher wages and higher hours, whereas the opposite is true for women. The motherhood hours gap is not affected by differences in occupation, education, and industry, but the motherhood wage gap is driven by differences in these characteristics.

There are four primary takeaways from our analysis of the labor market gender gap over the past 30 years. First, since 1980 there have been substantial reductions in the segregation of women into higher-education tracks and occupations, and to a lesser extent reductions in establishment-level segregation. Second, there has simultaneously been a reduction in the role of observable differences in education, occupation, industry, and experience in explaining the gender wage gap. Third, though there has been a dramatic reduction in the gender hours gap, this does not seem to be driven by desegregation: differences in the education, occupation, and industry explain virtually none of the gender hours gap both in 2010 and in past years. Differences in sorting at the establishment level does seem to explain about 30 percent of the gender hours gap consistently over time. Finally, motherhood predicts large differences in hours worked for women, and smaller differences in wages. The wage differences are largely accounted for by differences in occupation, education, and industry of mothers compared to non-mothers, while hours differences are not explained by these characteristics.

The remainder of this paper proceeds as follows: Section 2 describes the data used in calculations. Section 3 presents decompositions of earnings, hours worked, and wages over time and describes sorting patterns across occupations, industries, and workplaces. Section 4 concludes.

2. Data and sample selection

In this section we present the data used and our minimal sample selection.

Registers The data source for this paper is Danish administrative data primarily from the database IDA, which is a longitudinal register containing demographic information on the Danish population (such as gender and age) from 1980 to 2010. Labor market outcomes (such as employment, wages, and yearly earnings) for employed individuals, and identifiers for both the establishment and the firm (from 1995) in which a worker is employed can be observed and linked to the individual from 1980 and onwards using unique establishment and firm identifiers. Establishments and firms are connected to workers in the last week of November of every year.

Statistics Denmark creates a measure of hourly wages based on hours worked as estimated from mandatory 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, but finding reliable hours data is a general problem with most data sets. We have deflated earnings and wages according to the Danish 2012 consumer price index.

The register also includes information on industry, occupation, and municipality of work linked to establishment and individual identifiers. Occupation is the ISCO88 after 1990 and a measure of primary labor market attachment 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,

[1] For a discussion, see Brown (1980), Lucas (1977), and Hotz et al. (2017).

[2] Danish wage data is based on hours worked measurements from retirement contributions. Unfortunately, these are bracketed making wage estimates extremely noisy for workers working few hours (for example, 0–8 hours per week is one bracket). Statistics Denmark imputes wages primarily based on these retirement payments and creates a variable which assigns each wage and uncertainty flag. Most observations in which a worker works less than half time are flagged as low-confidence wage estimates. We do not use these wages in our analysis. This means we drop between 12 and 19 percent of observations with positive earnings in our main sample. We discuss below the reasons for our interest in wage decompositions, despite this data limitation.

Table 1
Sample summary statistics.

	1980	1995	2010
Female	0.42	0.45	0.50
	(0.49)	(0.50)	(0.50)
Age	39.59	40.98	43.12
	(9.86)	(9.52)	(9.57)
Experience	10.68	16.91	18.41
	(4.63)	(7.95)	(9.92)
Has children	0.75	0.76	0.76
	(0.44)	(0.43)	(0.43)
Cohabiting	0.09	0.17	0.18
	(0.29)	(0.37)	(0.38)
Married	0.71	0.60	0.57
	(0.45)	(0.49)	(0.49)
Has high school degree	0.40	0.47	0.44
	(0.49)	(0.50)	(0.50)
Has college degree or more	0.21	0.27	0.40
	(0.40)	(0.45)	(0.49)
Hourly wages (in 2012 DKK)	177.29	208.37	239.35
	(65.95)	(83.79)	(137.78)
Yearly earnings (in 2012 DKK)	289,382	320,341	388,255
	(136,150)	(153,774)	(245,404)
Weeks worked	49.8	49.5	49.24
	(8.09)	(8.41)	(9.32)
Observations	1,286,677	1,547,681	1,564,670

Note: This table summarizes key variables used throughout the paper in three key periods: 1980, 1995, and 2010. The population is all those between 25 and 60 working at least half-time and not in school in Denmark. Means and standard deviations (in parentheses) are reported.

which is consistent over time and can be used to obtain the expected duration and the type of schooling.

Sample Selection We impose a minimal set of sample selection criteria. In all years, we restrict our analysis to men and women between 25 and 60 years old. We include only workers who report positive total earnings, positive, high quality (as described above) wages, positive days worked per year, and who are not currently in school. We thus include most prime-aged workers in Denmark in order to get a view of the full economy.

Descriptive Statistics Table 1 summarizes key features of the sample over time. As in Table 1 we will in general focus on the years 1980, 1995, and 2010 in order to keep the number of estimates manageable. The average Danish worker in our sample is a little over 43 years old with 18 years of experience in 2010 (younger and less experienced in 1980). Most notably for our paper, there is a very large rise in the fraction of the population with a college degree in our data. While only 21 percent of the population in 1980 had a college degree, the fraction of the population with a college degree is 40 percent in 2010. The fraction of the half-time plus population which is female has risen as well, from 43 percent to 50 percent. Finally, we see that marriage rates have fallen while cohabitation rates have risen. The sum of marriage and cohabitation rates have only fallen by five percentage points (to 75 percent) over this period in our sample. We describe changes in the characteristics of the population in more detail in the next section, particularly how these changes affect relative wages.

3. Results

In this section we present our main analysis. We first document general trends in earnings, wages, and hours and show how labor market segregation has changed over our sample period. We proceed by exploring how the changes over time in the gender wage gap and the gender gap in working hours have been affected by the trends in labor market segregation and other observable characteristics. We conclude by discussing the lower hours and wages associated with motherhood and how different characteristics of workers impact parenthood gaps across gender and over time.

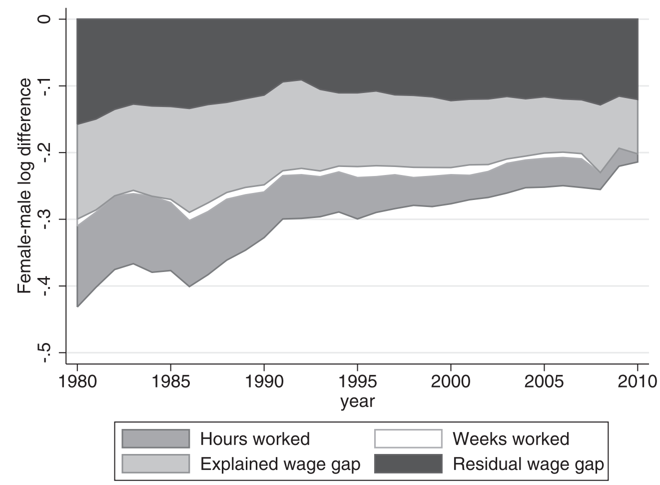

Fig. 1. Decomposition of the gender earnings gap.
Note: This figure plots the average log difference in labor market earnings between men and women ages 25–60, excluding those in school or working less than half time. We decompose this difference into weeks worked in the year, hours worked per week, wages, and wages residual of age, experience, occupation, and firm.

3.1. General trends

Fig. 1 plots the average log difference in earnings of men and women in our sample over time, and then decomposes this earnings gap into a portion explained by difference in log average hours worked (dark grey area), differences in log weeks worked (white area), and differences in log wages (light grey and black areas). Our measure of weeks worked excludes time when parents are on parental leave, as well as unemployment spells. The differences in log wages is further decomposed into the portion which can be explained by differences in worker age, experience, education, occupation, and the establishment where workers work (light grey area) and the residual gender wage gap (black area).[3] We measure experience as the sum of total hours worked over the lifetime. Education is measured as dummies which capture the interaction of broad major (humanities, social science, etc) cross level of education (technical school, college degree, masters, etc). Occupation is at the 3-digit ISCO level, and firm is a measure of the establishment (physical address) where a worker is employed.

The large earnings gap in 1980 shrinks substantially by 2010, but the decline in the wage gap is much smaller. The more than 10 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 equally by a reduction in the wage gap and a reduction in the hours gap.[4] The difference in average employment on the extensive margin (including both unemployment and parental leave in our measure of time away from work) is small and does not change substantially over time.

[3] The residual wage gap is the predicted difference in log wages of men compared to women in a regression of log wages which includes, in addition to a gender indicator, fixed effects for age, a cubic in experience, and indicators of 3-digit ISCO occupation level, 4-digit education level, and establishment ID. We run a separate regression in each year. For all other variables (for example, weeks worked), we simply let the area represented be the average log difference between men and women in our sample in each year.

[4] Though we restrict to half-time plus workers in this analysis, the reduction in the hours gap between men and women is a broader phenomenon. Considering the entire population of employed workers, the fraction of women working part time has fallen substantially over time, from nearly 40% in 1980 to 15% in 2010. The fraction of men working part time has slightly risen over time, from 8 percent in 1980 to about 12 percent in 2010, as shown in Appendix Fig. 6.

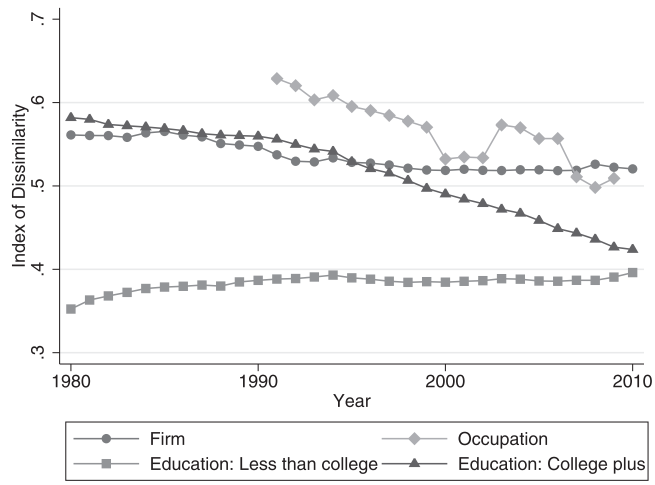

Fig. 2. Segregation by firm, occupation, and education over time.
Note: This figure plots the Duncan and Duncan (1955) index of dissimilarity—the sum over categories of the absolute difference in the fraction of men in a category minus the fraction of women in the category—for occupations (at the ISCO-88 3-digit level), firm establishments, and education groups (at the 4-digit level of major/specialization cross level). The education index is split into those education groups which correspond to some technical training or high-school and below-level degrees (labeled "less than college") and those education groups representing college degrees and above.

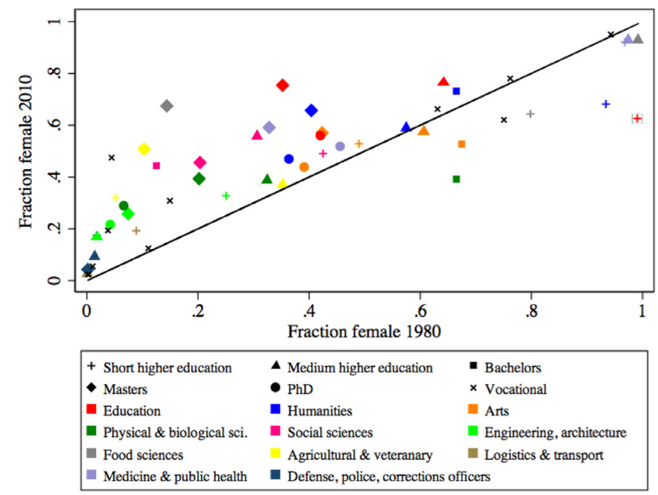

Fig. 3. Segregation by education track: 2010 vs. 1980.
Note: This figure is a scatter plot of the average fraction of an education type which is female in 2010 against the fraction female in 1980. The sample includes all Danes between 25 and 60 in 1980 and 2010 respectively. Education type is the highest level of education achieved over the (observed) lifetime and is defined as the product of education level (symbols) and major (shading). This is the four-digit level of the variable defined as hffsp by Statistics Denmark.

The decrease in the wage gap was driven by a decrease in the portion of the wage gap explained by other observable characteristics, such as education and experience. The wage gap residual of age fixed effects, a cubic in experience, as well as occupation, establishment, and education fixed effects is fairly constant over time.

We next turn to understanding how segregation in occupation, education, and workplace has evolved over time, and how this has impacted the gender wage gap. Fig. 2 plots the Duncan and Duncan (1955) segregation index for occupation, establishment, and for education (separately for the population with a college plus education and those with less education). This index measures the fraction of the population which would need to change occupations (or workplaces, or college majors) in order for each occupation (or workplace, or major) to reflect the gender ratio in the population. For each year t and each level l corresponding to firm, occupation, less than college education track, and college and above education track, Fig. 2 plots

$$d_{lt} = \frac{1}{2}\sum_{i=1}^{N_{lt}}\left|\frac{m_{it}}{M_t} - \frac{f_{it}}{F_t}\right| \tag{1}$$

where m_{it}/M_t is the fraction of the male population in category i of level l and f_{it}/F_t is the fraction of the female population in the same category. The absolute difference between population shares of men and women in each category is summed over all categories and divided by two. If the difference is zero, this reflects exactly equal female and male ratios across all categories, where a category refers to an individual establishment, an 3-digit ISCO-88 occupation, or a 4-digit education code, as noted in the corresponding figure notes.

Segregation has fallen dramatically in the college-plus education categories. Segregation is slightly increasing at below-college levels of education. As shown in Fig. 3 which plots the relative fraction of educations which is female, convergence has happened especially at the master's degree level. Fig. 3 plots the fraction female in a given education level and specialization. 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 observations lie above the 45 ° line reflects relatively more women getting educated.

Occupational segregation has also fallen over time, and by more than establishment level segregation.[5] The fraction of workers who would need to change jobs in order to within-workplace gender balances which mirror the gender balance of the working population has fallen by five percentage points (ten percent) since 1980. Occupation-level dissimilarity has fallen from more than 60% in the mid-90s to less than 50% in 2010.

Thus, at both the establishment and occupation level as well as for higher educations we see a pattern of desegregation over the last 30 years. The desegregation of higher education is particularly stark and suggests that high skilled women have access to increasingly varied post-education career opportunities.

3.2. *The gender wage gap*

How has this desegregation translated to wages? To study the role of differences in observable characteristics like occupation or education more formally, we next provide a Blinder-Oaxaca decomposition of log wages in 1980, 1995, and 2010. The Blinder-Oaxaca 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, and estimating the difference in wages which observables across gender evaluated at the female wage regression coefficients would predict. The Blinder-Oaxaca decomposition in Table 2 gives the log point difference in wages explained by differences in the average educational attainment, occupation, age, experience, and industry of men compared to women.[6] This is comparable

[5] The number of firms is not constant over time, which makes is somewhat difficult to compare segregation over time—adding categories can only cause segregation to increase—but this would not account for the large drop in segregation over time.

[6] The sample sizes differ slightly from those reported in the summary statistics because in this exercise we also restrict to occupation and education groups with at least 50 individuals of each gender. This is to avoid making inference from extremely noisy parameter estimates.

Table 2
Decomposition of the Gender Wage Gap: 1980, 1995, and 2010.

Year	1980	1995	2010
Male log(w_i)	5.249	5.381	5.503
	(0.000)	(0.000)	(0.000)
Female log(w_i)	4.949	5.160	5.301
	(0.000)	(0.000)	(0.000)
Difference	0.300	0.221	0.202
	(0.001)	(0.001)	(0.001)
Total explained	0.167	0.124	0.075
	(0.001)	(0.001)	(0.001)
Experience	0.046	0.025	0.008
	(0.000)	(0.000)	(0.000)
Industry	0.055	0.073	0.069
	(0.001)	(0.001)	(0.001)
Education	0.014	0.008	-0.014
	(0.001)	(0.001)	(0.001)
Occupation	0.056	0.023	0.017
	(0.000)	(0.001)	(0.001)
Age	−0.003	−0.001	0.000
	(0.000)	(0.000)	(0.000)
Total unexplained	0.133	0.097	0.127
	(0.001)	(.0.001)	(0.001)
N^m	738,518	850,543	775,640
N^f	547,573	696,573	788,461

Note: 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 female log wage coefficients. Industry is the difference in two-digit industry code indicators evaluated at the female log wage coefficients. Education is the difference in four-digit educational attainment indicators (which includes both years of schooling and type of schooling) evaluated at the female log wage coefficients. In 1995 and 2010, occupation is the difference in three-digit ISCO indicators evaluated at the female log wage coefficients. In 1980, occupation categories are blue collar, white collar, high-skilled, and management. Finally, age is the difference in age indicators evaluated at the female log wage coefficients.

to the decomposition highlighted in Blau and Kahn (2016) for the case of the US.

In general, we see that differences industry, occupation, and experience explain a large part of the gender wage gap. Differences between men and women in education and age do not contribute to understanding differences in the gender wage gap, conditional on occupation, industry, and experience. What remains of the gender wage gap in 2010 cannot easily be explained by age, occupation, experience, or education differences between men and women. Notice that differences in industry still plays a role and in total observable differences explain 7.5 percentage point of the 20.2 percent wage gap in 2010. This contrasts with the 1990s and 1980s when about 15 percentage points of the gap could be explained by differences in these variables.[7]

We take advantage of our data, which includes establishment identifiers, to further decompose the wage gap and to study how important observable characteristics have been over time for the population overall, for young people, and for parents compared to non-parents. We plot the results of a Blinder-Oaxaca decomposition of log wages in 1980, 1995, and 2010 into components explained by differences in the establishments where workers are employed (labeled firm), their labor market experience, their occupation, and their education in Fig. 4. Everywhere, the decomposition is implemented using estimates from a regression of female wages in our sample overall on cubics in age and experience, and indicators of 3-digit ISCO occupation level, 4-digit education level, and establishment ID so that coefficients are consistent across subgroups. We find that the patterns in the data overall (generally a fall in the role of observable characteristics) are mirrored across subgroups, but that in general fathers and mothers have the largest differences in these characteristics. For non-parents, none of the difference in male-female wages can be attributed to the sum of differences in sorting on education, firm, and occupation in 2010. The same is largely true of young people (though there is more firm-level sorting for this group), but this is not true of parents.

Unlike all other characteristics, differences in the establishments where women work compared to the establishments where men work have not fallen (as a factor explaining wage differences) since 1995. We now turn to a more detailed analysis of the role of establishment-level sorting on the gender wage gap, which the work of Card et al. (2016) made central to recent discussion of the gender wage gap. In order to understand how the types of establishments in which women work compared to establishments in which men work may differ, and how this has changed over time, we begin by following methods described in Card et al. (2016) (henceforth CCK) to run a gender-specific worker-establishment fixed effects decomposition of wages. The goal of this analysis is to understand whether women are working in establishments which pay lower wages on average.

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 establishment ID is available since 1980 and consistent over time. We estimate an additive two-way fixed effects model as developed in Abowd et al. (1999)—an AKM model. As in CCK, all coefficients are allowed to vary by gender. More specifically, we estimate

$$w_{it} = \alpha_i + \phi^{G(i)}_{J(i,t)} + X'_{it}\beta^{G(i)} + r_{it} \tag{2}$$

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. Eq. (2) 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 six regressions of the form (2). We discuss the assumptions under which estimates of establishment effects are unbiased and details of the estimation in the Appendix.[8]

After estimating establishment effects by gender from Eq. (2), we can decompose the average difference in these effects into: i) what women would be paid if they worked at the establishments men work at (a sorting effect), and ii) what women would be paid at their own workplaces if they were men (what CCK refer to as a bargaining effect):

$$\begin{aligned} E[\phi^M_{J(i,t)}|m] - E[\phi^F_{J(i,t)}|f] &= \left\{ E[\phi^M_{J(i,t)} - \phi^F_{J(i,t)}|m] \right\} \\ &\quad + \left\{ E[\phi^F_{J(i,t)}|m] - E[\phi^F_{J(i,t)}|f] \right\} \end{aligned} \tag{3}$$

The first term in this equation is the bargaining effect and the second term is the sorting effect. We cannot meaningfully estimate the bargaining effect without anchoring the establishment fixed effects from the female and male regressions. Establishment fixed effects are otherwise only estimated relative to some omitted category which must contain the same set of workplaces in both the female and male regressions. CCK uses value added data to do this and empirically argues that low value added firms have the same firm effect for men and women. However, we cannot do this, since we do not have value added data going

[7] Discrimination may contaminate estimates of the role of observables. In particular, the coefficients from the female regressions may be “too small” because of discrimination. If discrimination has fallen over time, then our estimates overstate the role of falling segregation on the wage gap. In this case, however, we would also expect the unexplained portion of the wage gap to fall over time. This has not happened in Denmark.

[8] For criticisms and a detailed discussion see Lamadon et al. (2015), Lentz (2010), Eeckhout and Kircher (2010), Lopez de Melo (2018), Hagedorn et al. (2017), and Bagger and Lentz (2014).

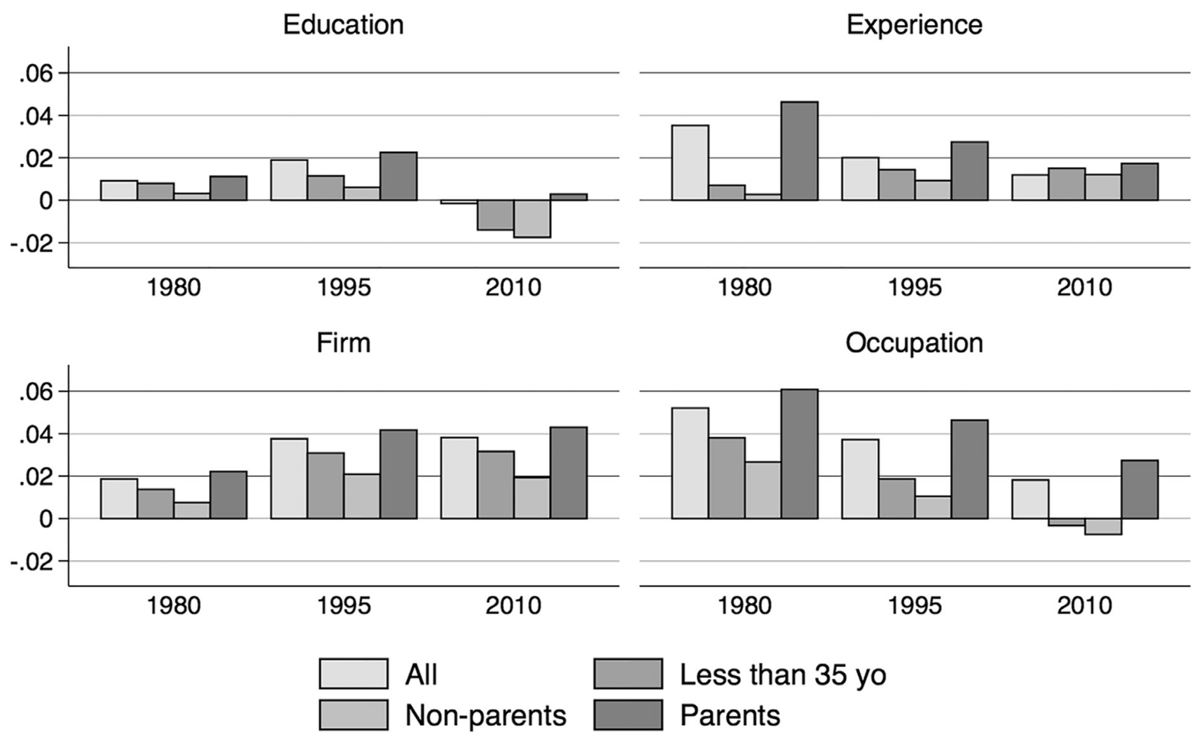

Fig. 4. Blinder-Oaxaca Decomposition over Time.
Note: This figure plots the log-points of the gender wage gap explained by education (at the 4-digit level of major cross level), experience (years in the labor market), firm establishment, and occupation (at the 3-digit ISCO-88 level post 1991 and in coarse skill categories before that) for O-B decompositions of wages in 1980, 1995, and 2010. These decompositions also include age fixed effects, but conditional on experience age plays no role in the gap and we omit it in this figure. The returns to various characteristics are calculated on the female sample and categories which do not include both men and women are dropped. In addition to plotting contribution of various differences in characteristics in the full sample (”All”), we also plot the log point differences in subsamples of the population: workers less than 35 years old, non-parents, and parents.

back to 1980. Since the sorting term uses only the fixed effects from one regression and takes a difference, it is invariant to the normalization or anchoring.

The AKM decomposition captures establishment effects which are invariant to the worker composition of the firm. This is not the case when estimating establishment fixed effects without also including individual fixed effects as long as there is unobservable individual heterogeneity, which is correlated with establishment effects. As we believe this is the case, the AKM decomposition is an improvement over the Blinder-Oaxaca decomposition including establishment fixed effects, though the specifications are quite similar. The large role for establishments, which we found in Fig. 4, may in part capture unobserved permanent characteristics of workers in the firm. This is not the case when including individual fixed effects. Otherwise, this decomposition is analogous to a Blinder-Oaxaca decomposition.

Table 3 summarizes the difference in establishment-level sorting by gender over time, relative to the log-point difference in wages by gender. This method gives results broadly consistent with Fig. 4: despite the small reduction in establishment level segregation over time, differences in where women work explain more of the wage gap over time. While in the 1980s just under ten percent (2.6 log points) of the wage gap could be attributed to women working in lower-pay establishments, in the 2000s this explains about 15 percent (3.3 log points) of the wage gap.

Our findings imply that the characteristics of the establishments employing women have changed over time, as measured by average wages. We also documented in Fig. 1 that hours worked are an important component of the gender earnings gap (on average in the 2000s there is a 4.5 log point difference in hours worked between half-time plus men and women). We next turn to understanding how gender segregation and changes in gender segregation over time have impacted the gender hours gap and what the role of establishments is in this gap.[9]

3.3. The gender hours gap

A number of recent papers document gender differences in the value of non-work time and in preferences for shorter hours (Hotz et al., 2017; Mas and Pallais, 2017; Forthcoming; Wasserman, 2017), and as noted in Blau and Kahn (2013), a greater prevalence of part time work among women is a key difference between labor markets in Europe compared to the US. As discussed, the prevalence of part time work among women has fallen substantially over the past 30 years in Denmark, as has the role of differences in hours in explaining the gender wage gap. Is this because sorting of women into different educations, occupations, and establishments has declined as documented in Fig. 2 or is it just an overall trend?

We replicate the same Blinder-Oaxaca decomposition for hours as we had for wages for the years 1980, 1995, and 2010. The results are shown in Table 4. We find that industry, education, and occupation explain none of the gender hours gap in 1980, 1995, or 2010. Indeed, these factors would predict that women work more hours than men, on average. Differences in experience play some role in 1980, where it explains

[9] While in general high-wage firms are also low-hours firms, this correlation is weaker in the set of firms where women work compared to the set of firms where men work (-0.3 in 2010 compared to -0.36). The negative correlation is in part mechanical—any sample deviations in estimates of firm effects in hours will also show up negatively in wages—but is also consistent with OLS estimates in the compensating differentials literature which yield a robustly positive relationship between wages and non-wage benefits in the cross-section (see for example Brown, 1980; Lucas, 1977).

Table 3
Establishment Effects and the Gender Wage Gap.

	1980–1989			
	Sorting		Log wages	
	$\hat{\phi}^F\|f$	$\hat{\phi}^F\|m$	$\log(w^f)$	$\log(w^m)$
Average effects	0.086	0.112	5.001	5.282
Difference ($f-m$)		−0.026		−0.27
	1990–1999			
	Sorting		Log wages	
	$\hat{\phi}^F\|f$	$\hat{\phi}^F\|m$	$\log(w^f)$	$\log(w^m)$
Average effects	−0.306	−0.274	5.157	5.383
Difference ($f-m$)		−0.032		−0.225
	2000–2009			
	Sorting		Log wages	
	$\hat{\phi}^F\|f$	$\hat{\phi}^F\|m$	$\log(w^f)$	$\log(w^m)$
Average effects	0.016	0.049	5.232	5.44
Difference ($f-m$)		−0.033		−0.208

Note: This table presents average establishment fixed effects in the female and male population (respectively), using the female-only AKM decomposition described in the text. The difference between average establishment fixed effects ($\hat{\phi}F$) in the male and female population summarizes the amount of sorting in the labor market. Average log wage differences are displayed in the last two columns. We estimate the AKM model using log wages separately for male and female workers between 25 and 60, excluding those who are not working in the largest connected set, for each decade 1980–1989, 1990–1999, and 2000–2009.

Table 4
Decomposition of the Gender Hours Gap: 1980, 1995, and 2010 .

Year	1980	1995	2010
Male log(h_i)	7.412	7.329	7.365
	(0.000)	(0.000)	(0.000)
Female log(h_i)	7.280	7.250	7.352
	(0.000)	(0.000)	(0.000)
Difference	0.132	0.078	0.012
	(0.001)	(0.001)	(0.000)
Total explained	0.042	0.021	−0.008
	(0.001)	(0.001)	(0.001)
Experience	0.073	0.038	0.010
	(0.000)	(0.000)	(0.000)
Industry	−0.018	0.008	0.007
	(0.000)	(0.001)	(0.001)
Education	0.004	−0.009	−0.015
	(0.001)	(0.001)	(0.001)
Occupation	−0.011	−0.016	−0.010
	(0.000)	(0.001)	(0.001)
Age	−0.006	0.000	0.001
	(0.000)	(0.000)	(0.000)
Children	0.000	0.000	−0.001
	(0.000)	(0.000)	(0.000)
Total unexplained	0.090	0.058	0.020
	(0.001)	(0.001)	(0.001)
Children	0.014	0.027	0.016
	(0.000)	(0.000)	(0.000)
N^m	738,518	850,539	775,640
N^f	547,573	696,573	788,461

Note: 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 female log hours coefficients. Industry is the difference in two-digit industry code indicators evaluated at the female log hours coefficients. Education is the difference in four-digit educational attainment indicators (which includes both years of schooling and type of schooling) evaluated at the female log hours coefficients. In 1995 and 2010, occupation is the difference in three-digit ISCO indicators evaluated at the female log hours coefficients. In 1980, occupation categories are blue collar, white collar, high-skilled, and management. Finally, age is the difference in age indicators evaluated at the female log hours coefficients.

Table 5
Establishment Effects in Hours and the Gender Hours Gap.

	1980–1989			
	Sorting		Log hours	
	$\hat{\phi}^F\|f$	$\hat{\phi}^F\|m$	$\log(h^f)$	$\log(h^m)$
Average effects	−0.532	−0.499	7.256	7.367
Difference ($f-m$)		−0.033		−0.11
	1990–1999			
	Sorting		Log hours	
	$\hat{\phi}^F\|f$	$\hat{\phi}^F\|m$	$\log(h^f)$	$\log(h^m)$
Average effects	0.459	0.488	7.256	7.324
Difference ($f-m$)		−0.028		−0.069
	2000–2009			
	Sorting		Log hours	
	$\hat{\phi}^F\|f$	$\hat{\phi}^F\|m$	$\log(h^f)$	$\log(h^m)$
Average effects	0.125	0.142	7.313	7.358
Difference ($f-m$)		−0.017		−0.045

Note: This table presents average establishment fixed effects in the female and male population (respectively), using the female-only AKM decomposition on hours described in the text. The difference between average establishment fixed effects ($\hat{\phi}F$) in the male and female population summarizes the amount of sorting into firms based on the hours they typically offer. Average log hours differences are displayed in the last two columns. We estimate the AKM model using log hours separately for male and female workers between 25 and 60, excluding those who are not working in the largest connected set, for each decade 1980–1989, 1990–1999, and 2000–2009.

7.3 log points of the hours gap. The decrease in the explained part from 4.2 log points in 1980 to -0.8 log points in 2010 is entirely driven by the decreasing differences in experience between men and women. Notice, that some of this is partly automatic because experience measures total accumulated hours worked over the labor market career.

We now replicate the CCK analysis on hours. Table 5 shows the role of sorting at the establishment level and it turns out that there is some role for establishments in explaining the gender hours gap. This table presents average establishment level hours, residual of individual fixed effects, estimated from the female-only for men, $\phi^{\hat{F}}|m$, compared to women $\phi^{\hat{F}}|f$. The difference gives the effect of establishment-level sorting on the gender hours gap, and the effect is not negligible. In the 1980s 3.3 log points of the 11 log point gender hours gap could be attributed to women working in lower-hours workplaces. In the 2000s, the relative role of establishment-level sorting has remained 30 percent, though the level of the hours gap has fallen.

While differences in education and occupation do not predict the hours gaps between men and women, establishment differences do explain some of the gap. There are no differences in the fraction of women compared to men with children, but there are major differences between parent vs. non-parents by gender. The last row of Table 4 includes the gender difference in the hours gap between parents an non-parents. This has played an relatively increasing role in total differences in hours worked, despite being fairly stable over time.

3.4. Parenthood

We can see the relative importance of motherhood in understanding the persistence of the gender wage gap in the raw data. Fig. 5 plots the wage gap in Denmark, by cohort birth year (plotting the cohort born every ten years from 1930 to 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 study of cohorts over the lifecycle reveals two important trends. First there has been a fall in the wage gap at (almost) every age over time and wage gaps are u-shaped over the lifecycle. For cohort born in 1960, a wage gap of less than 20 log points at age 25 increased to 25 log points over the next 15 years at which point it began to rise again.

Table 6
The motherhood penalty and fatherhood premium over time.

Year	1980		1995		2010	
	Women's hours					
Has Children	−0.1422*** (0.0014)	−0.0772*** (0.0014)	−0.1282*** (0.0015)	−0.1206*** (0.0014)	−0.0753*** (0.0011)	−0.0857*** (0.0018)
	Women's wages					
Has Children	−0.0143*** (0.0015) [423588]	−0.0341*** (0.0011) [423588]	−0.0693*** (0.0009) [497792]	−0.0150*** (0.0008) [497792]	−0.0461*** (0.0011) [512169]	−0.0143*** (0.0015) [512169]
	Men's hours					
Has Children	0.0330*** (0.0009)	0.0104*** (0.0008)	0.0267*** (0.0015)	0.0012 (0.0010)	0.0288*** (0.0011)	0.0079*** (0.0013)
	Men's wages					
Has Children	0.0687*** (0.0009) [548305]	0.0491*** (0.0009) [548305]	0.0898*** (0.0012) [581058]	0.0533*** (0.0009) [581058]	0.0898*** (0.0012) [521823]	0.0543*** (0.0014) [521823]
Expanded controls	N	Y	N	Y	N	Y

Note: This table displays results of regressions of men's and women's log hours and log wages on an indicator of whether the individual is a parent for each year 1980, 1995, and 2010. We present both regressions which only include age fixed effects (labeled no controls) and regressions which include education dummies (major cross level completed), three-digit ISCO occupation fixed effects, industry fixed effects, a cubic in experience, and age fixed effects. Standard errors are in parentheses and number of observations are in brackets.

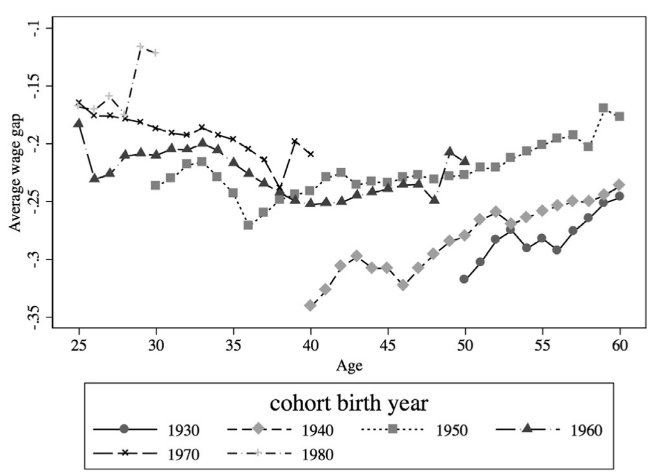

Fig. 5. Raw wage gap in Denmark, by cohort.
Note: This figure plots the average log difference in wages of women compared to men over their working life (25–60) by birth cohort. The sample is Danes woking at least half-time and not in school who are born in 1930, 1940, 1950, 1960, 1970, and 1980.

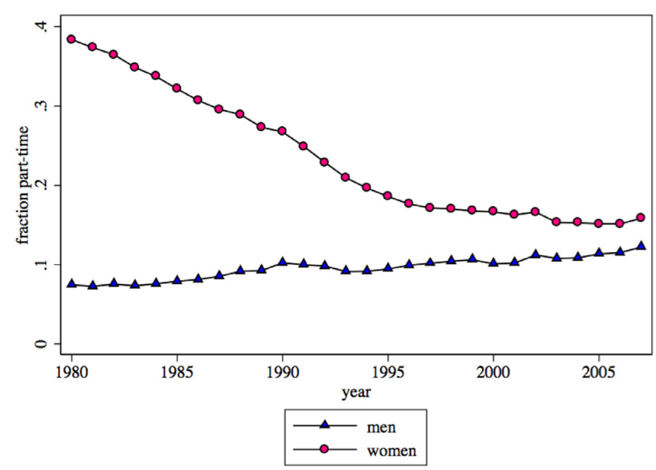

Fig. 6. Part-time work in Denmark since 1980.
Note: This figure plots the fraction of men (triangles) and women (circles) working less than full time (37 hours per week) in Denmark.

As described in Kleven et al. (Forthcoming), these parenthood gaps rise discontinuously when women have children. Kleven et al. (Forthcoming) use an event-study framework to analyze the lifetime costs of children and describe how it has changed from 1980 to the present day. 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 percent in 1980 to 20 percent in 2013. The overall earnings penalty is 19.4 percent 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. A number of other papers similarly study the parenthood 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.

To better see the effects of parenthood on wages and hours we first turn to Table 6, which plots regression coefficients on an indicator of whether a worker has children from a regression of hours and wages for women 25–45 years old,[10] both with and without additional controls. In the second panel, we present the same results for men. While men's hours are not affected by children, women's hours are substantially affected by children. For women, having children is associated 9 percent

[10] We exclude older workers because they generally have older children no longer in the home. The results are robust to including older workers but are muted.

lower hours in 2010. The effect was 8 percent in 1980 and 12 percent in 1995. Controls for education, experience, occupation, and industry do not affect this motherhood hours gap. In contrast, men with children work more, on average, than men without children, but only be one percentage point.

The effect of parenthood on wages is smaller than the effect of parenthood on hours for women, but larger for men. Without including controls for differences in experience, education, occupation, and industry, wage regressions suggest about a five percentage point parenthood gap for women. Including controls, the gap is smaller, consistent with what we would expect from the larger role of differences in characteristics for parents in the Blinder-Oaxaca decompositions in Fig. 4. For men, the parenthood wage gap is 9 percent without controls and 5 percent with controls. This has been remarkably stable since 1995.

The impact of adding controls for industry, occupation, experience and education on motherhood wage and hours gaps over time is consistent with the relative role of these characteristics in explaining wage and hours gender gaps: they do not impact hours, but they do somewhat explain wage differences. In 1995 and 2010, mothers work fewer hours across the board compared to non-mothers, but differences in observables do generate a substantial fraction of the smaller motherhood wage penalty.

4. Conclusion

We show that from 1980 to 2010 in Denmark, labor markets have become less gender segregated and at the same time, the gender earnings gap has significantly decreased. A growing body of research studies the relationship between these two facts. The gender earnings gap has fallen over time in Denmark for two reasons. First, the portion of the wage gap explained by differences in education, experience, occupation, and industry of women compared to men has fallen since the 1980s by nine log points. Second, there has been a reduction of similar size of the gender hours gap. We find no difference in the residual wage gap over the period. The reduction in the gender hours gap cannot be explained by a reduction in segregation at the education track or occupation level. There is, however, a non-trivial role for firms in the gender hours gap: women work in establishments where a given worker has 2–3% fewer hours, on average, compared to establishments where men work.

Segregation at the establishment level has fallen over time but not by as much as segregation in occupation or in education track for high-skilled workers. Differences in establishment-level sorting explain about three percentage points of the gender wage gap, similar to results reported in Card et al. (2016) for Portugal. The reduction in the hours gap is not driven by occupation and education choices, even in 1980 when both the hours gap and segregation were large. We document a large (relative) role of establishment-level sorting for the hours gap, which is consistent with the hours preferences of women relative to men as suggested, for example, by Wasserman (2017) who studies residency choices of female doctors after the imposition of hours restrictions on shifts and Wiswall and Zafar (2018) who study the stated preferences of college graduates, finding that women have a greater willingness-to-pay for hours flexibility.

Differences in occupation, employer, education, and experience imply the largest gender wage gap for mothers compared to the rest of the population. Differences between mothers and women without children in these characteristics also account for most of the motherhood wage penalty. Occupation, firm, and education choices do not account for a substantial portion of the nine percent motherhood hours gap.

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Appendix A

A1. AKM-decomposition and assumptions

In this section, we describe in more detail the assumptions behind the AKM decomposition of log wages which we present estimates of in Table 3. The AKM model relies on a set of strong assumptions. Two of these are linearity of wages in person and firm fixed effects and the assumption of exogenous mobility. Loosing speaking the exogenous mobility assumption implies that workers cannot move based on the error term. The main criticism of this is that the error term will encompass any match effects and that it seems very likely that workers will make job decisions based on these. In unreported results we follow (Card et al., 2013) and show that workers moving from the fourth quartile to the first quartile in the firm effect distribution have roughly the same wage decreases as workers moving from the first quartile to the fourth quartile have as wage increases. This is true across quartile pairs and for both men and women. This suggests that match effects are not large in the data and thus any violation of the exogenous mobility assumption is going to play a minor role. A second support of the linear model without any match effects can be found in the recent work by Lamadon et al. (2015). They propose a mixture model with a finite number of worker and firm types, but allow arbitrary wage schedules within each worker-firm pair. What they find is that wages are almost linear in firm types even though the model in no way imposes this. Another main criticism against the AKM model has arisen from the theoretical search literature. Lentz (2010), Eeckhout and Kircher (2010), Lopez de Melo (2018), Hagedorn et al. (2017), and Bagger and Lentz (2014) all point out that the worker fixed effect in the AKM regression might not capture the underlying worker type very well. This is a concern that one cannot directly test without a structural model and something that one should have in mind when using the AKM framework. However, e.g. Bagger and Lentz (2014) conclude that their estimated structural model is largely consistent with the AKM model, so it is not conclusive that the AKM model is wrong.

We can decompose the average difference in establishment-effects for women compared to men into a sorting component and a bargaining component.[11] After estimating firm effects by gender from Eq. (2), we can decompose the average difference in firm effects into: i) what women would be paid if they worked at the firms men work at (a sorting effect), and ii) what women would be paid at their own firms if they

[11] 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

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

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

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

After estimating τ and by-gender firm effects from Eq. (2), 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.

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 3gives 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.

A2. Appendix figures

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