Reaching the Top or Falling Behind? The Role of Occupational Segregation in Women's Chances of Finding a High-Paying Job Over the Life-Cycle

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Abstract

Using a two-stage decomposition technique, this paper analyzes the role of occupational segregation in explaining the probability of women vis-à-vis men of finding high-paying jobs over the life-cycle. Jobs are classified as highly-remunerated if their compensation exceeds a threshold, which is set at different values to span the entire wage distribution. Results obtained from pooled CPS surveys indicate that the importance of occupational segregation remains virtually unchanged over the life-cycle for low- and middle-wage workers. However, women's access to high-paying occupations becomes significantly more restricted as workers age, suggesting a previously undocumented type of 'glass ceiling' in the U.S.

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Keywords: Occupational segregation, glass ceiling, life-cycle career, gender wage gap.

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1 Introduction

It has been argued that most of the gender wage gap is the result of women having more difficulties than men in climbing the career ladder. For example, Lazear and Rosen (1990) seminal paper states that *"Female wages are lower because they are less than proportionately represented on higher-paying jobs. Within jobs, men and women are compensated according to the same formula."*(page S108). At face value, this statement says that occupational segregation, when narrowly defined, should account for the totality of the gender wage gap. Moreover, the same paper also concludes that *"A woman must have greater ability than a man to be promoted. Some women are denied a promotion that goes to a lower ability man."*(page S108) implying that as men and women of equal ability spend time on the labor market, the gender wage gap is expected to increase as a result of exclusively a rise in occupational segregation. Among other things, the results presented below suggests that Lazear and Rosen (1990) statements have no empirical support for most of the workers. Nonetheless, they are partially valid among the highly remunerated.

Despite the extensive literature on the topic, the contribution of occupational segregation to the relative chances of women's finding high-paying jobs as they age has not been thoroughly documented. This is surprising considering that the uneven distribution of female and male workers across job types explains a remarkable share of today's average gender pay gap (Blau and Kahn (2017), Goldin (2014)). Tackling this issue, this paper aims to answer the following questions: given workers with identical observable characteristics, what is the differential probability that women earn remunerations located above certain threshold in relation to their men counterparts? and how much of this relative probability is explained by occupational segregation as workers age?

The empirical approach in this paper modifies existing decomposition techniques to answer these questions. Contrary to previous methods that deal with *unconditional* differences in wages between men and women, this method decomposes the gender wage gap *conditional* on observable characteristics of workers. Stated differently, this method decomposes a coefficient of interest obtained from a regression framework into *'mediators'*. Here, the coefficient of interest is the one associated with a gender dummy variable in a regression that models the probability of earning high wages. The estimated gender gap from this regression is further decomposed into an occupational segregation component and a within-occupation gender inequality component.

The method proposed here is a two-step procedure. The first stage models the allocation of men and women into different occupations given a set of observable characteristics. The second stage uses the predictions of the first stage to decompose the conditional gender gap. The method in this paper is strongly related to the classical Oaxaca-Blinder decomposition (Blinder (1973), Oaxaca (1973), Fortin et al. (2011)), however its interpretation is different. The O-B technique aims to explain why an outcome of interest differs between two groups of individuals (men and women in this case) by partitioning the total observed gap into differences in observable characteristics or determinants of the outcome and differences in the "returns" to these characteristics. On the other hand, the conditional decomposition proposed here aims to answer the question of why the outcomes of observationally identical men and women differ. Is it because they are allocated to different occupations or because the are remunerated differently within each occupation?

The decomposition technique used in this paper has strong similarities to that in Gelbach (2014). However, the estimator and the question of interest slightly differ. Gelbach's paper proposes a technique to account for the impact of adding regressors on a coefficient of interest in a regression framework. His method solves the main problem of traditional approaches: the order in which a sequential inclusion of extra covariates is done affects the final conclusion of a regression analysis.

Decomposing the relative female chances of earning high wages requires a narrow definition of occupations and a relatively large number of workers in each of them. This paper pools several years of the Current Population Survey data and classifies workers into seventy-seven occupations consistently defined since 1979. Nonetheless, the results are highly robust to different classifications of occupations. The most disaggregated one classifies workers into specific 'jobs', which are defined as industry-occupation combinations (e.g., a bus driver working for a school is treated differently than a bus driver working for the urban transit system).

Classifying jobs as 'highly-remunerated' is certainly arbitrary. For this reason, this paper does it using a variable threshold that spans the entire wage distribution, allowing the visual analysis of the relative female chances of working in high-paying positions when the threshold to classify them becomes more stringent.

This paper provides a rich description of the relative female probabilities of working in highly-remunerated positions. The most salient finding is in relation to the evolution of the role played by occupational segregation over the life course. Women's probabilities of working in a job that pays 'well' relative to observationally similar men declines with age. This fact is true irrespectively of the threshold use to classify well-paying jobs, which is consistent with previous evidence for the average gender wage gap (Goldin (2014)). However, the decline in the relative female chances of being highly remunerated along their career is *virtually zero* explained by changes in occupational segregation everywhere in the wage distribution except for the job positions located at the top. Since, as discussed below, gender differences in career progression and changes in occupational segregation are related, then this finding appears to contradict the general presumption that the widening of the gender pay gap as workers age is the consequence of women climbing the career ladder at a slower pace.

Although the gender occupational segregation does not change as workers age for most of the wage distribution, it strongly increases its explicative power at the very top. The relationship between the changes in the occupational segregation component over the life-cycle and the threshold used to classify high-paying jobs have a clear break (or 'kink') at the 0.8 quantile of the wage distribution. Below this point, the magnitude of occupational segregation is identical for early-career workers (25 to 29 year-olds) and late-career workers (55 to 59 year-olds). Above this point, the gender occupational segregation among 'late-career' workers becomes significantly higher. For example, the probability that women earn wages at the top five percent of the distribution in relation to comparable men declines twenty percentage points over the life-course. Almost *all* of it is explained by increments in occupational segregation as workers age.

The increase in the occupational segregation at the top of the wage distribution over the life-cycle suggests the presence of a glass ceiling in the U.S. labor market. Interestingly, within-occupation gender wage inequality tends to decline in highly remunerated jobs partially counterbalancing the glass ceiling effect on wages. Thus, women appear to have lower chances of accessing high-paid positions in their life. However, when they obtain such positions, they are equally remunerated than men.

This paper contributes to the literature on gender occupational segregation and to the literature on female 'glass ceiling' - i.e., the implicit differential barriers that women face to advance in their careers. In relation to the occupational segregation literature, this study departs from most others in two dimensions. Firstly, it analyzes occupational segregation as a 'mean' rather than as an 'end'. That is, it quantifies the contribution of occupational segregation to the relative female chances of earning high wages. It does not attempt to measure the degree of occupational segregation per se, as done it by several valuable papers in the literature (e.g., Blau et al. (2013), Levanon et al. (2009), Gross (1968), Jacobs (1989), Blau and Hendricks (1979), Bianchi and Rytina (1986), Beller (1985), Blau et al. (1998), Cotter et al. (1995)). Secondly, previous papers that analyze the role of occupational segregation on wages tend to do it performing decompositions of the unconditional average gender wage gaps, neglecting potential differences between highly-remunerated jobs and other jobs in the economy (e.g., Goldin (2014), Bayard et al. (2003), Macpherson and Hirsch (1995)). However, there are exceptions. In addition to computing a standard Oaxaca-Blinder decomposition, Blau and Kahn (2017) decompose the unconditional gender gap at different percentiles of the wage distribution. They find that the gender pay gap explained by covariates (including occupational dummies) fell approximately in the same proportion at any point of the wage distribution between years 1980 and 2010. But, the 'unexplained' component of the decomposition declined less than proportional among top earners. The method used by Blau and Kahn (2017) answer a different question that the one posted here. Nonetheless, they also suggest the possibility of a 'glass ceiling' for women.

The literature on 'glass ceiling' is precisely the second area of research that this paper contributes to. A set of papers estimates wage equations using the quantile regression technique to measure the gender wage gap across the wage distribution. For example, Albrecht et al. (2003) show that gender wage differentials in Sweden increase throughout the quantiles of the wage distribution with an acceleration of the incremental rate at the top. They interpret this fact as evidence of a 'glass ceiling'. A regression specification that includes occupational dummies results in similar conclusions. Arulampalam et al. (2007) and De la Rica et al. (2008) also compute quantile regression in a similar way than Albrecht et al. (2003), but for different countries.

The papers that estimate wage equations using quantile regressions provide a very valuable contribution to the literature on 'glass ceiling'. Nonetheless, they present two shortcomings. On the one hand, the method used is highly sensitive to transformations of the dependent variable (e.g., using pre-tax wages or post-tax wages). Second, these papers do not show results for workers at different stages of their career. A 'glass ceiling' is expected to become apparent as workers age and some of them (presumably women in larger proportions) fail to reach highly-ranked job positions. These two drawbacks are discussed in more detail below.

The rest of the paper is as follows. Section 2 discusses alternative ways of measuring the existence of a 'glass ceiling' and the drawback of such approaches. Section 3 explains the conditional decomposition used in this rest of the paper. Section 4 describes the data, variable definitions and provides summary statistics. Section 5 presents the main results of this paper. It also analyzes the gender segregation in executive occupations, and shows that the 'glass ceiling' is exclusively a phenomenon of college educated workers. Section 6 uses the narrowest feasible definition of occupation in the data, which is computed as the combination of industry and occupation. Section 7 discusses the robustness of the results to alternative regression specifications and variable definitions. Section 8 concludes.

2 Glass ceiling: concept and measurement

2.1 The concept of glass ceiling

It is generally agreed that the concept of 'gender glass ceiling' refers to the barriers or extra difficulties that women face to advance in their careers at the same pace as men do. Empirically, previous papers have examined two processes to identify the existence of a glass ceiling. These processes are related but different in nature. The first one gives the 'glass ceiling' an occupation or job hierarchy interpretation by studying the relative likelihood that women get promoted. The papers in this research area usually analyze promotion probabilities in panel data (e.g., Addison et al. (2014), Blau and DeVaro (2007), Booth et al. (2003), Javdani and McGee (2015), Hersch and Viscusi (1996)); although few do it by analyzing the implications in a static context (Winter-Ebmer and Zweimüller (1997)). The second approach gives the 'glass ceiling' a remuneration interpretation. Paper using this approach study the gender wage gap across the distribution generally using quantile regressions (Albrecht et al. (2003), Arulampalam et al. (2007), De la Rica et al. (2008)).

In an extreme case, one may think that there is a one-to-one relationship between the frequency in which a worker is promoted and his/her position in the wage distribution. This is the idea of Lazear and Rosen (1990) when they claim that *"within jobs, men and women are compensated according to the same formula."* and that *"female wages are lower because they are less than proportionately represented on higher-paying jobs"*. However, previous evidence suggests that the magnitude of the wage increment associated with a promotion can be very different for men and women (Addison et al. (2014), Hersch and Viscusi (1996), Booth et al. (2003), Javdani and McGee (2015)), and that gender differences at the top of the wage distribution remain important even when measured among workers in the same job/occupation (Blau and Kahn (2017), Albrecht et al. (2003)).

The two interpretations of the 'glass ceiling' are important, and the relationship between them should be carefully analyzed. This paper sheds light on this issue. It studies the gender gap in the probabilities of earning high wages and the role played by job/occupational segregation.

Section 3 describes the empirical strategy used in this paper. It is different from the conventional quantile regression used in the literature previously mentioned. The reason to change the approach is that the quantile regression suffers the methodological problem of not being invariant to transformation of the dependent variable. The issue is described below.

2.2 The use of quantile regression to evidence the presence of a 'glass ceiling'

Previous papers aiming to reveal the existence of a 'glass ceiling' have extensively used a quantile regression approach (e.g., Albrecht et al. (2003)). However, the results obtained with this methodology are sensitive to transformations of the dependent variable, in particular to the way in which wages are measured. This methodological drawback raises a concern of how robust its conclusions are and evidences the need for an alternative approach.

The point just mentioned can be illustrated as follows. Let y^{pretax} be a variable measuring the logarithm of pre-tax wages, fem an indicator variable that takes the value one if the worker is female and zero if not, and x a set of covariates. A quantile wage equation is usually modeled as follows:

$$Q_\tau(y^{pretax}|fem, x) = \beta_0(\tau) + \beta_1(\tau)fem + \beta_2(\tau)x \tag{1}$$

where $Q_\tau(y^{pretax}|fem, x)$ is the conditional quantile τ of pre-tax wages, which is usually assumed to be a linear function of the regressors. The coefficients of interest are $\beta_1(\tau)$ for different quantiles, (i.e., values of $\tau \in [0, 1]$). When estimates of $\beta_1(\tau)$ disproportionately increase in absolute terms at the top of the distribution making the function $\beta_1(\tau)$ convex in τ, then it is interpreted as evidence of a 'glass ceiling'.

Figure 1 shows the pattern of results just described. The x-axis measure the conditional quantile (τ) and the y-axis the estimated coefficients $\beta_1(\tau)$ obtained from a set of quantile regressions as (1). The upper curve shows the estimates for simulated pre-tax wages. The data were generated to mimic the quantile profile usually found in the literature. The widening of the gender wage gap at the top of the distribution is interpreted as evidence of a 'glass ceiling'.

The drawback with this approach is that the convexity of the quantile curve used to evidence the presence of a 'glass ceiling' is not robust to most transformations of the dependent variable. For example, if instead of computing the quantile regression using pre-tax wages, one uses post-tax wages in an economy with a progressive tax system, then the convexity of $\beta_1(\tau)$ in relation to τ may disappear. Figure 1 exemplifies this case. The lower curve shows quantile regression results after applying the same progressive tax scheme to both, female and male wages. Although the quantile curve remains increasing across the distribution, there is no acceleration at the top, implying no glass ceiling for after-tax wages.

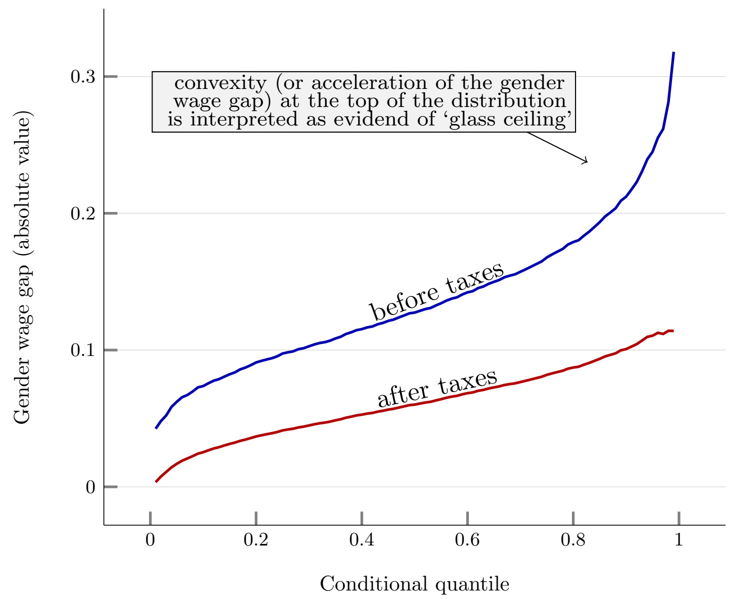
The conditional quantiles will usually differ for pre-tax y^{pretax} and post-tax $y^{posttax}$ wages.

$$Q_\tau(y^{pretax}|fem, x) \neq Q_\tau(y^{posttax}|fem, x) \tag{2}$$

The exception is when the tax rate in the economy is the same for all workers. However, this case is extremely rare. Most of the countries impose higher tax rates to highly-remunerated individuals.[1]

[1]With a flat tax rate the relationship between log pre-tax wages and log post-tax wages is $y^{pretax} + ln(1 - t) =$

Figure 1: Quantile regression results before and after progressive taxes
(simulated data)



The lack of consistency to transformations of the dependent variable that characterizes the quantile regression approach does not imply by any means that the conclusions obtained in previous papers are incorrect. On the contrary, some of them (e.g., Albrecht et al. (2003)) perform convincing robustness analyses. Nonetheless, the use of quantile regressions should be applied with caution in this literature. The next section presents a simple method that is robust to any increasing (i.e. rank-invariant) transformation of the dependent variable.

3 Empirical strategy

This section is divided in three parts. Firstly, it introduces a linear probability model used to identify the women's relative chances of working in a highly paid position. Secondly, it shows a two-step decomposition procedure used to analyze how much of these relative chances are explained by gender occupational segregation and how much by within-occupation gender wage inequality. Finally, this section explains how the decomposition technique is used to study the evolution of gender disparities in the access to high-paying jobs over the life-cycle.

$y^{posttax}$, where t is the common tax rate for all individuals. The additive term $ln(1-t)$ that differentiate pre- and post-tax wages only affects the intercept of regression (1). The slope $\beta_1(\tau)$ is unchanged.

3.1 Reaching the top: women's relative chances

Consider the linear probability model (3).

$$
\begin{aligned}
y_i^c &= \beta_0 + \beta_1 fem_i + x_i\beta_2 + \epsilon_i \qquad (3) \\
y_i^c &= \begin{cases} 1 & \text{if } wage_i > c, \\ 0 & \text{if } wage_i \leq c, \end{cases}
\end{aligned}
$$

The dependent variable y_i^c is an indicator that takes the value one if the wage level of individual i is above a threshold c and zero otherwise. The regressors in equation (3) include a female indicator fem_i and variables contained in the row vector x_i that potentially affect the worker's remuneration, such as age, education and race. The coefficient of interest is β_1. It measures the relative probability that woman i vis-à-vis an observationally identical man earns a remuneration above threshold c.

A caveat to this framework is that the threshold c used to determine when a remuneration is 'high' is arbitrary. A simple solution adopted here is to estimate regression (3) for different values of c spanning the entire wage distribution and report the full set of results.

Two specification adjustments ease its interpretation. First, the set of c values are chosen to be the quantiles of the male wage distribution. That is, $c(\tau) = F^{-1}(\tau|fem = 0)$, where $F^{-1}(\tau|fem = 0)$ is the inverse of the cumulative distribution of male wages evaluated at the τ^{th} quantile. For example, $c(0.9)$ is the wage level above which the top 10% of men's remunerations lie. The values of $c(\tau)$ used in the estimation procedure correspond to $\tau \in \{0.02, 0.04, ..., 0.96, 0.98\}$. Second, the dependent variable is divided by $1 - \tau$, which is the proportion of male workers with wages above $c(\tau)$. For notational convenience, this transformation of the dependent variable is denoted $\omega_i^\tau \equiv \frac{y_i^{c(\tau)}}{(1-\tau)}$. As a result of these two adjustments, the estimating system of equations becomes:

$$
\begin{aligned}
\omega_i^\tau &= \beta_0^\tau + \beta_1^\tau fem_i + \beta_2^\tau x_i + \epsilon_i^\tau \qquad (4) \\
& for\ each \quad \tau \in \{0.02, 0.04, ..., 0.98\}
\end{aligned}
$$

The coefficient of interest β_1^τ identifies the differential gender probability *in percentage terms* of working in a job that pays more than $c(\tau)$. For example, ${\beta_1}^{0.9} = -0.57$ indicates that the chances of a woman receiving a wage in the top 10% of the male wage distribution is 57% lower than that of a man with identical observable characteristics. This can be shown formally as follows - the subscript i in variables is ignored to simplify the notation.

$$
\begin{aligned}
\beta_1^\tau &= E(\omega^\tau|fem = 1, x) - E(\omega^\tau|fem = 0, x) \\
&= \frac{E(y^{c(\tau)}|fem = 1, x) - E(y^{c(\tau)}|fem = 0, x)}{(1-\tau)} \\
&= \frac{P(y > c(\tau)|fem = 1) - P(y > c(\tau)|fem = 0)|x}{P(y > c(\tau)|fem = 0)} \qquad (5)
\end{aligned}
$$

Because β_1^τ is a proportion, it is bounded between -1 and 1. If no woman earns above $c(\tau)$, then $\beta_1^\tau = -1$ (women are 100% less likely to earn above $c(\tau)$). If men's and women's wages have equal chances of being above $c(\tau)$, then $\beta_1^\tau = 0$. If $\beta_1^\tau > 0$, then there is a larger proportion of women than men above $c(\tau)$.

Invariability of results to rank-preserving transformations Notice that setting the thresholds $c(\tau)$ as quantiles of the unconditional male wage distribution implies that the results are invariant to any transformation of wages that preserve the rank of individuals. For example, computing regression (4) using either pre-tax or post-tax wages yields the same results as long as taxes do not invert the order of any two workers in relation to their income. Taxes decrease both wages and the thresholds $c(\tau)$ in the same way. All workers whose pre-tax wages are below the quantile $c(\tau) = F^{-1}_{pretax}(\tau|fem = 0)$ for any τ, also have post-tax wages below the quantile $c'(\tau) = F^{-1}_{posttax}(\tau|fem = 0)$, and vice versa, where $F^{-1}_{pretax}(\tau|fem = 0)$ and $F^{-1}_{posttax}(\tau|fem = 0)$ are the inverse functions of the pre-tax and post-tax male wage distribution respectively. As indicated in the previous section, this methodological property is desirable when the tax system is highly progressive.[2,3]

3.2 Conditional decomposition and occupational segregation

The coefficient β_1^τ in regression (4) measures the relative probability that a woman vis-a-vis an observationally identical man receives a high remuneration. The next question is: how much of this differential probability can be attributed to occupational segregation an how much to within-occupation gender inequality? This section proposes a two-stage conditional decomposition to answer it.

Let z_i be a $L-1$-dimensional column vector containing dummy variables for the L occupations in the economy excluding one, the omitted category. That is, if individual i works in occupation l, then the l-entry of vector z_i takes the value one and the rest of the entries take the value zero. If this individual is in occupation L, the omitted one, then all entries of z_i are zero. The choice of the omitted category does not affect the results. Consider augmenting regression (4) with occupational dummies interacted with gender indicators.

$$\omega_i^\tau = \alpha_0^\tau + \alpha_1^\tau fem_i + \alpha_2^\tau x_i + \underbrace{\gamma_0^\tau((1-fem_i)\times z_i) + \gamma_1^\tau(fem_i \times z_i)}_{extra\ terms\ in\ relation\ to\ regression (4)} + \mu_i^\tau \tag{6}$$

Take the expectation of (6) conditional on x_i but not on z_i separately for men and women.

$$E(\omega_i^\tau|fem_i = 1, x_i) = \alpha_0^\tau + \alpha_1^\tau + \alpha_2^\tau x_i + \gamma_1^\tau E(z_i|fem_i = 1, x_i) \tag{7}$$

$$E(\omega_i^\tau|fem_i = 0, x_i) = \alpha_0^\tau + \alpha_2^\tau x_i + \gamma_0^\tau E(z_i|fem_i = 0, x_i) \tag{8}$$

The difference between equations (7) and (8) is precisely the coefficient β_1^τ in regression (4) and

[2]Notice that a progressive tax is a rank-preserving transformation.

[3]The invariability of results to rank-preserving transformation is valid when the thresholds $c(\tau)$ a transformed in a similar way than the wage variable. If instead of using the quantiles of the unconditional male distribution, one uses the quantile of the male distribution conditional on a set of variables, then the results also applies. For example, the $c(\tau)$ can be the quantiles of the male, white, non-Hispanic wage distribution.

can be written as follows.

$$\beta_1^\tau = E(\omega_i^\tau | fem_i = 1, x_i) - E(\omega_i^\tau | fem_i = 0, x_i) \tag{9}$$

$$= \underbrace{\alpha_1^\tau + (\gamma_1^\tau - \gamma_0^\tau) E(z_i | fem_i = 1, x_i)}_{\textit{within-occupation gender inequality}} + \underbrace{\gamma_0^\tau [E(z_i | fem_i = 1, x_i) - E(z_i | fem_i = 0, x_i)]}_{\textit{cond. occupational segregation}} \tag{10}$$

Expression (9) is readily obtained from the conditional expectation of equation (4), while expression (10) is the result of subtracting (8) to (7) and do the appropriate algebraic manipulation. The right-hand side of (10) is almost identical to the Oaxaca-Blinder decomposition. However, it departs from this one in two dimensions. First, the decomposition is performed on a regression coefficient (β_1^τ), rather than on the unconditional average gap of the dependent variable. Second, the average characteristics z_i of the two groups of interest (women and men in this case) are computed *conditional* on a set of variables x_i.

The interpretation of decomposition (10) is as follows. The lower probability of finding women in job positions that pay above $c(\tau)$ in relation to observationally identical men (i.e. the left hand side β_1^τ) can be explained by an uneven allocation of similar workers across occupations z_i (i.e. the conditional occupational segregation component) and by gender wage differentials among comparable workers within each occupation (i.e. the within-occupation gender inequality component)

The computation of decomposition (10) requires the estimation of the conditional expectations $E(z|fem, x)$. This can be done is a separate step computing a set of auxiliary regressions.

$$z_i = \delta_0 + \delta_1 fem_i + \delta_2 x_i + error \tag{11}$$

The system (11) contains $L-1$ equations, one for each occupation in the vector z_i. Then, δ_0 and δ_1 are $L-1$-dimensional column vectors and δ_2 is an $(L-1 \times k)$ matrix of coefficients. Replacing the expectations $E(z|fem, x)$ obtained from equations (11) in the decomposition (10) gives a simple expression for the conditional occupational segregation component.

$$\textit{cond. occupational segregation} = \gamma_0^\tau [E(z_i | fem_i = 1, x_i) - E(z_i | fem_i = 0, x_i)] \tag{12}$$

$$= \gamma_0^\tau \delta_1 \tag{13}$$

The *within-occupation gender inequality* component in decomposition (10) is obtained by computing the difference $\beta_1^\tau - \gamma_0^\tau \delta_1$ or by estimating an additional set of auxiliary regression.[4,5]

The two stages of the decomposition have a clear interpretation. The first stage, regression (11), computes the gender differences in the allocation of workers across occupations. The second stage, regression (6), measures the compensations of each occupation across genders conditional on workers' characteristics. First and second stages combined (expression (10)) decomposes the total gender gap in the regressions of interest (4).

Two remarks worth mentioning. First, the decomposition (10) is exact in the sense that the left-hand side obtained from estimating regression (4) is numerically identical to the right-hand side obtained by combining the coefficients of (6) and (11). This is true because the specification of auxiliary regressions (11) is identical to the specification of the equation of interest (3) (i.e., same regressors with the same functional form in a linear projection). Second, the conditional decomposition (10) simplifies to the standard of Oaxaca-Blinder technique when no x_i variables are included. This result is expected and desirable from a statistical perspective. A conditional approach like the one presented here should reduce to an unconditional one when the conditioning set is empty.

3.3 A life-cycle perspective

The decomposition (10) can be computed for young workers who are in their early stages of their career path and for older workers who have been two or three decades in the labor market. The comparison of these two groups of workers is essential to reveal the existence of a 'glass ceiling'. The presumably lack of opportunities for women in the labor market is expected to emerge progressively over time.

[4] Notice that the conditional expectation of equation (6) can be rewritten as

$$E(\omega_i^\tau | fem_i, x_i) = \alpha_0^\tau + \alpha_1^\tau fem_i + \alpha_2^\tau x_i + \gamma_0^\tau E(z_i | fem_i, x_i) + (\gamma_1^\tau - \gamma_0^\tau) E((fem_i \times z_i) | fem_i, x_i)$$

The conditional expectation on the right-hand side can be computed with the help of auxiliary regressions

$$\begin{aligned} z_i &= \delta_0 + \delta_1 fem_i + \delta_2 x_i + error \\ fem_i \times z_i &= \phi_0 + \phi_1 fem_i + \phi_2 x_i + error \end{aligned}$$

The first of these auxiliary regressions is as before, where

$$\delta_1 = E(z_i | fem_i = 1, x_i) - E(z_i | fem_i = 0, x_i)$$

The second auxiliary regression, which dependent variable is the product of z_i and the female indicator gives:

$$\begin{aligned} \phi_1 &= E(fem_i \times z_i | fem_i = 1, x_i) - E(fem_i \times z_i | fem_i = 0, x_i) \\ &= E(z_i | fem_i = 1, x_i) \end{aligned}$$

Then, within-occupation gender inequality in (10) is

$$\begin{aligned} within - occupation\ gender\ inequality &= \gamma_1^\tau - \gamma_0^\tau) E(z_i | fem_i = 1, x_i) \\ &= (\gamma_1^\tau - \gamma_0^\tau)\phi_1 \end{aligned}$$

The previous expression is numerically identical to $\beta_1^\tau - \gamma_0^\tau \delta_1$.

[5] Expression (13) is almost identical to that in Gelbach (2014). Although in his paper, the added covariates are included in levels, not interacted with the female indicator, which gives a different interpretation of results.

Denote the components of the decomposition W = *within-occupation gender differences* and S = *conditional occupational segregation*. Then, the decomposition for early-career workers and for late-career workers can be written as follows.

$$\beta^{\tau}_{1(early\ career)} = W_{(early\ career)} + S_{(early\ career)}$$
$$\beta^{\tau}_{1(late\ career)} = W_{(late\ career)} + S_{(late\ career)}$$

The change over the life-cycle in the relative women's probabilities of working in a high-paying position is:

$$\beta^{\tau}_{1(late\ career)} - \beta^{\tau}_{1(early\ career)} = (W_{(late)} - W_{(early)}) + (S_{(late)} - S_{(early)}) \tag{14}$$

The thresholds used to determine high-paying jobs are age-specific. For example, if $\tau = 0.9$, then the threshold $c(0.9)$ in regression (4) is the 0.9 quantile of the early-career male wage distribution when β^{τ}_{1early} is computed and the 0.9 quantile of the late-career male wage distribution when β^{τ}_{1late} is computed. Then, $\beta^{0.9}_{1\ early}$ is the relative probability that *young* women earn wages in the top 10% of the *young* male wage distribution, and $\beta^{0.9}_{1\ late}$ is the relative probability that *middle-aged* women earn wages in the top 10% of the *middle-aged* male wage distribution. Setting age-specific thresholds $c(\tau)$ facilitates the comparison of workers of similar characteristics over the life-cycle (e.g., approximate years in the labor market).

4 Data and descriptive statistics

The data source is the Annual Social and Economic Supplement of the Current Population Survey (i.e., CPS-March) obtained from Ipums-CPS (Flood et al. (2018)). The data is pooled in four ten-year time periods 1979-1988, 1989-1998, 1999-2008 and 2009-2018. This aggregation responds to the need of having an 'acceptable' number of observations in each narrowly defined occupational category.

Occupational classification The classification of occupations used in this study is obtained from the original CPS 1990-basis occupational scheme. Some of the occupations are not consistently defined over the years or contain very few workers in spite of pooling the data in ten-year periods. For this reason, the preferred occupational classification in this paper consists of grouping or aggregating occupations in the following way.

The CPS 1990-basis occupational scheme provides different levels of aggregation. For example, the occupation *'civil engineer'* belongs the set of occupations classified as *'engineers'*, this group belongs to a supra-group called *'professional Specialty Occupations'* and this latter group to a more aggregated one labeled *'managerial and professional specialty occupations'*. Most of the results shown below use occupations that are grouped to the immediately higher level of aggregation. For example, *'civil engineers'* are bundled together with the rest of engineering specialties into the CPS first level of aggregation *'engineers'*. The result of this procedure is a classification consisting of seventy-seven occupations consistently defined over time (see Appendix IV for details).

The specific classification of occupations used in the decompositions has the risk of affecting the conclusions. In addition the preferred grouping of occupations just described, all results are computed with two more disaggregated schemes. One of them is the original 394 categories provided by the CPS in its 1990-basis scheme (see Appendix IV). This more disaggregated classification has the advantage of being narrower. However, the comparability across decades is compromised to some extent. For example, post-secondary teachers are classified by the subject they teach only until 2002.

The narrowest classification of workers used in the paper defines 'jobs' as combinations of industries (CPS-1990 scheme) and occupations (CPS-2010 scheme), both in their most disaggregated version. For example, a bus driver working for a school is treated differently than a bus driver working for the urban transit system. The 'jobs' analyzed are those for which at least ten female workers and ten male workers are sampled in each survey year. Since multiple years are pooled together, the resulting observation per job is above one hundred per sex. The workers in industry-occupation cells that do not satisfy the minimum number of observations are drop from the sample when this classification is used. The grouping of workers into 'jobs' - as just defined - can be consistently done for years 2011 to 2018. The results presented below are extremely robust to the occupational classification used.

Wages and wage quantiles The dependent variable in the regression (4) is an indicator that takes the value one if the wage of the individual is above a specified threshold level. Wages are defined as CPI-index deflated pre-tax annual earnings (wage and salary income) divided by annualized hours worked.

The top coding applied to the CPS data (i.e., the process of replacing extreme values of the income distribution with lower ones) practically does not affect the dependent variable. The top codes are located at or above the 99 percentile of the income distribution. This value is larger than the threshold used to build the dependent variable. However, the top coding applies to annual income. When this variable is divided by the hours worked, some top coded values may fall at lower percentiles of the *wage* distribution. Despite this concern, results shown in the Appendix are strongly robust to the top coding procedure.

The final caveat in relation to the dependent variable in regression (4) is that the thresholds $c(\tau)$ are the quantiles of the unconditional male distribution for the specific survey year when the workers was interviewed. That is, if a worker appears in the 2016 CPS, his/her income is compared to the quantile $c(\tau)$ of the male wage distribution in the CPS 2016 to determine if the dependent variable ω_i^τ is either zero or one for him/her. Computing $c(\tau)$ in each specific year eliminates the influence of aggregate shocks.

Appendix I shows summary statistics for the samples used in the analysis.

5 Results

5.1 Women's relative chances of reaching the top

Figure 2 shows the set of estimates for $\widehat{\beta}_1^\tau$ in regression (4) as a function of quantiles τ of the unconditional male wage distribution. Each curve in the graph represents a ten-year time period. Each point in the curves is obtained from a separate regression. For example, the value -0.71 corresponding to $\tau = 0.8$ in the period 1979-1988 is the estimate β_1^τ from equation (4) after defining that a worker is paid a 'high wage' if his/her remuneration is above the quantile 0.8 of the male wage distribution. The standard errors used to compute the 95% confidence bands are computed with 200 bootstrap replications. All points in the curves are estimated in each bootstrap replication, allowing to estimate the variance-covariance matrix of $\widehat{\beta}_1^\tau$ across quantiles.[6]

In addition to the female indicator, regressions (4) include covariates for age, four dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and three race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. Thus, the results are gender differences among similar workers. The sample used in the analysis contains all workers with positive earnings who were 25 to 64 years old when the survey was conducted.

The results indicate that the relative probability of women working in high-paying jobs tends to decline with the threshold used to classify jobs as such. For example, in 2009-2018 a female worker was 39% less likely than a comparable male to be paid above the median of the men's wage distribution. However, she was 50% less likely to obtain a position which remuneration lied at the top 20% of this distribution.

The comparison of different time periods in Figure 2 evidences the tendency for women's wages to catch up with men's wages at all points of the distribution. Most recent curves are located almost entirely above more distant ones. The larger improvement in female wages occurred between periods 1979-1988 and 1989-1998, particularly in the access to jobs located at the top 40% to top 30% of the male distribution.

5.2 The role of occupational segregation in women's relative chances of earning high wages

Figure 3 shows the results of computing the conditional decomposition in equation 10. The total relative female probability curve is identical to the 2009-2018 curve in Figure 2. The remaining curve located above it indicates the portion explained by occupational segregation at each quantile. For example, the probability that a woman earned a wage located at the top 20% of male wage distribution was 50% lower than the probability of a man with the same formal education, age and

[6] In each bootstrap replication, equation (4) is estimated for forty nine different threshold values $c(\tau)$ that corresponds to the quantiles $\tau = 0.02, 0.04, ..., 0.98$ of the unconditional male distribution. Thus, in each replication a 49×1 vector of $\widehat{\beta}_1^\tau$ is obtained. With the 200 replications a 49×49 variance-covariance matrix V is estimated. The representative element $\widehat{V}(i,j)$ is the estimate $\widehat{cov}(\widehat{\beta}_1^{i/50}, \widehat{\beta}_1^{j/50}) = \frac{1}{200}\sum_{k=1}^{200}(\widehat{\beta(k)}_1^{i/50} - \widehat{\beta}_1^{i/50})(\widehat{\beta(k)}_1^{j/50} - \widehat{\beta}_1^{j/50})$, where $\widehat{\beta(k)}_1^{i/50}$ is the estimate of $\beta_1^{i/50}$ (e.g., if $i = 3$, then $\tau = i/50 = 0.06$) obtained from the k bootstrap replication.

race. Fifteen percentage points of this gap are explained by occupational segregation and the rest, thirty-five percentage points, by within-occupation gender inequality.

The ratio of the two curves in Figure 3 indicates the proportion of the gender gap explained by occupational segregation. This ratio is presented in Figure 4 for this and all other periods in the study. Figure 5 shows decomposition curves analogous to those in Figure 3 used to plot Figure 4.

Occupations segregation explains 30% of women's lower probability of working in a high-paying job in the period 2009-2018. This number is remarkably stable regardless of the threshold used for the definition of high-paying jobs. However, this pattern has not been always such.

Figure 4 shows that in the period 1979-1988, occupational segregation explained a much smaller portion of gender wage differentials at the bottom of the distribution. The increase of the relative importance of the occupational segregation component at the left tail of the distribution over the years indicates that the decline in gender inequality within occupations has been more than proportional to the decline in occupational segregation in low-paying positions.

5.3 Occupational segregation over the life-cycle and the female chances of working in high-paying positions

If men are more likely to be promoted over their careers, then the gender occupational segregation is expected to increase over the life-cycle. Although not all promotions involve changing occupations, some of them do it. For example, a *salesman* can become a *supervisor of sales jobs*, and then a *manager* over time. These three job positions are identified as different occupations in the data.

This section performs decomposition (10) for early-career workers (25 to 29 years old) and for late-career workers (55 to 59 years old) separately. Subsequently, it performs the life-cycle decomposition (14) to investigate the evolution of the occupational segregation and the within-occupation gender inequality component as workers age.

Figure 6 is built in a similar way than Figure 3 but for different age groups. The thresholds used to classify high remunerations are age-specific. Thus, in panel a) the x-axis indicates the quantiles of the male wage distribution at ages 25 to 29 and in panel b) the quantiles of the male wage distribution at ages 55 to 59 . The age-specific threshold facilitates the comparison of female and male workers at similar points in their careers. For example, panel a) shows that 25 to 29 years old female workers have 33% fewer chances of earning remunerations in the top 20% of the male wage distribution **in the same age group.** As workers reach the age of 55 to 59 years old, panel b) indicates that such probability (the one corresponding to obtaining wages located at the top 20% of the male distribution **in their age group**) is 49% lower for women.

Panels a) and b) in Figure 6 show that occupational segregation is very different at the top of the wage distribution as workers age. Among early-career workers, the gender differences in the probability of earning very high wages for their age group are almost entirely explained by within-occupation gender inequality. Occupational segregation plays a minor role. For example, the gender occupational segregation explains virtually zero points of the lower female chances of earning wages located at the top 5% of the male wage distribution when young. However, among late career workers, occupational segregation plays a much relevant role at the top of the wage distribution. When workers are 55 to 59 years old, the gender occupational segregation component explains more than 20 percentage points of the lower female chances of earning wages located at the top 5% of the male wage distribution for this age group.

Figure 7 shows a clearer exposition of the evolution of occupational segregation over the life-cycle. It is the component $(S_{(late)} - S_{(early)})$ in (14), which is computed as the difference in the occupational segregation curves of panel b) and panel a) in Figure 6. The result is remarkable. For almost all quantiles, the occupational segregation component does not change as workers age. For example, at ages 25 to 29 female workers had 33% lower probability of earning wages at the top 20% of the male wage distribution. 12.7 percentage points of this gap corresponds to occupational segregation. At ages 55 to 59, the probability of earning wages at the top 20% of the male wage distribution becomes 49% lower for female workers, a significant change. However, occupational segregation explains 12.15 percentage points, which is almost identical to the portion explained at younger ages.

The zero change in occupational segregation over the life-cycle for wages below the 0.8 percentile suggests that the increment in gender wage inequality over the life-cycle cannot be explained by different rates of promotions for men and women, at least for most of the workers. This result emerges as a contradiction to previous ideas in the literature (e.g., Lazear and Rosen (1990)). Nonetheless, occupational segregation significantly changes over the life-cycle among workers located at the top of the wage distribution.

Figure 7 clearly shows that the evolution of the occupational segregation component over the life-cycle is markedly different at the top. The break in the trend at the 0.8 quantile is evident. While none of the decline in the female chances of being remunerated at the top 20% of male distribution can be attributed to changes in occupational segregation over the life-course, **all** of the life-cycle decline in the female chances of finding a job at the top 5% of the male distribution is attributed to an increase in the gender occupational segregation.

Figure 7 also shows a linear trend with an estimated break to rule out the possibility that the conclusions are the result of impressions of the data. The trend line with break point is the result of estimating a linear spline with an endogenous knot (see Appendix I for details). The estimated coefficient for the spline shows that the break in the trend is significant at 1%.

Can the trend break in Figure 7 be interpreted as evidence of a glass ceiling? The answer to this question remits to the discussion in Section 2. If the concept of glass ceiling is understood as the lack of female opportunities to move up in the career ladder, particularly to reach the top, then Figure 7 suggests that such constrains exist.

The presence of a glass ceiling is usually interpreted a form of gender discrimination imposed by employers towards employees. Nonetheless, part of the observed occupational segregation can be the result of workers self-selecting into different occupations for a variety of reasons, such as taste differences as the standard compensating differential theories establish or for family responsibility reasons as Goldin (2014) suggests. Similarly to previous papers in the literature, the self-selection component cannot be disentangled from the employer's imposed glass ceiling.

The increasing role of occupational segregation over the life-cycle to explain the lower probability of finding women at the top of the wage distribution is compensated with a decline in the within-occupation gender inequality. The upper left graph in Figure 8 shows the total change in the female chances of earning above quantile τ over the life-cycle. It is computed as the difference is the lower curves shown in panels b) and a) in Figure 6 and corresponds to the left-hand side of equality (14). The components of the decomposition into changes in within-occupation gender inequality (first term in the right-hand side of equality (14)) and changes in the gender occupational segregation (second term in the right-hand side of equality (14)) are shown in the second and the third graphs in the first row of Figure 8.

Remarkably, within-occupation gender inequality declines over the life-cycle at the top of the distribution. Notice that the withing-occupation inequality curve shows the component of the decomposition, which is computed as female workers in relation to male worker.For this reason is the negative value of the gender inequality. That is, the increasing at the top of the distribution towards zero implies a decline in within-occupational wage inequality. The occupational segregation, as previously explained, significantly increases (the third graph is identical to Figure 7). All results combined indicate that women have fewer chances of obtaining occupations with a remuneration that lies at the top of the wage distribution. However, once they obtain such job positions, their compensation tends to be the same as that for men.

The rest of the graphs in Figure 8 show decompositions for all the time periods included in this paper. The increase of the gender occupational segregation as workers age at the top of the wage distribution is evident in all years since 1979.

5.4 Executive, administrative, and managerial occupations

The general presumption is that the 'glass ceiling', if it exists, should be the result of women's lack of access to managerial positions.

Figure 9 shows the evolution of occupational segregation over the life-cycle as in Figure 7 but considering only two 'occupations': i) executive, administrative, and managerial occupations as defined in CPS (see Appendix IV), and ii) the rest of the occupations.

Classifying workers in only two categories eliminates the lack of robustness resulting from arbitrary choosing the omitted group when more than two categories are considered and the goal is to quantify the explanatory magnitude of a single occupation (see Fortin et al. (2011) and Ransom and Oaxaca (2005)). In previous sections, this issue was not a problem since a global value of occupational segregation was computed (Fortin et al. (2011) equation 19).

As expected, gender segregation in executive, administrative, and managerial occupations plays a larger role at the top of the wage distribution. In the period 1979-1988, eleven percentage points of the life-cycle decline in the female probability of earning a wage at the top 5% of the male wage distribution can be attributed to women being underrepresented in executive positions. Over the years, the gender segregation from managerial jobs have declined in more than half. However, there has been no change in the last twenty years.

Considering that gender occupational segregation explains twenty percentage points of the lower female chances of receiving wages above the 0.98 quantile (Figure 7), the 5 percentage points explained by gender segregation in executive, administrative, and managerial occupations represents an important component, but unable to explain the majority of the effect.

5.5 Formal education and occupational segregation over the life-cycle

Figure 10 shows the evolution of the gender occupational segregation over the life-cycle in a similar way than Figure 7. However, the graphs are computed separately for college-educated workers and the rest.

The results are striking, the 'glass ceiling', defined as the increasing role of occupational segregation at the top of the wage distribution, is strong for college-educated. Among workers with incomplete college or less formal education, the occupational segregation component does not change at any point in the wage distribution. The two graphs in the figure suggest that the 'glass ceiling' is mostly the result of college educated male worker accessing highly-paid occupations as they age. These occupations appear to be significantly less populated by college-educated women and worker with less than a B.A. degree.

6 A very narrow classification of occupations

A coarse definition of occupations may underestimate the role of the gender occupational segregation in explaining the lower probability of observing women at the top of the wage distribution. This section uses the narrowest possible definition in the CPS data. A 'job type' is defined as a combination of the occupation and the industry of the worker. For example, a bus driver working for a school is considered to be in a different 'job type' than a bus driver working for the city transportation system.

In principle, there could be thousands of job type defined in this way. However, most of these 'cells' are empty or contain an insufficient number of workers. As a result, only 'jobs' containing at least ten male workers and ten female workers per year are considered. Since many years of the CPS data are pooled for the analysis, each job type contains more than one hundred workers per sex. The final number of job types in the analysis is 221. The complete list is in Appendix III.

Workers in a job type that does not satisfy the minimum required number of observations are dropped from the sample. Thus, the classification of occupations in this section prioritizes the consistency of the definition rather than the population representativeness of the sample.[7]

Figure 11 shows the results of a decomposition similar to that in Figure 3 but using the narrow classification of occupations just described. The total effect curves (the set of $\widehat{\beta_1^\tau}$) are very similar in Figures 11 and 3 indicating that dropping some workers from the sample affects little the relative

[7] This is the same as imposing a common support for the comparison of individuals across groups (Fortin et al. (2011)).

female probability of receiving a high remuneration. This fact is desirable to compare the role of occupational segregation across classifications.

The narrow definition of occupations (i.e. job types) increases the explicative power of the gender occupational segregation. However, more than half of the female probability of receiving a high remuneration remain explained by within-occupation gender inequality.

Figure (12) replicates Figure (7) using the new narrow classification of occupations. Similar to the results in the previous section, the gender occupational segregation explains nothing of the female decline in the probability of earning high wages over the life-cycle until the quantile 0.7. However, the occupational segregation plays an important role in explaining the decline in female chance over the life-cycle of receiving a remuneration located at the top of the distribution.

7 Robustness of results

The conclusions obtained from previous results are strongly robust to alternative regression specifications and variable definitions. Appendix II show robustness results by changing three dimensions of the analysis. Firstly, all regressions are computed using the original CPS-1990 occupational classification scheme. Secondly, the definition of early-career and late-career workers is modified. In addition to comparing 55-59 years old worker to 25-29 years old workers, the appendix shows results comparing 60-64 years old workers to 25-29 years old worker, and 60-64 years old workers to 30-34 years old workers. Finally, Appendix II shows that the results are not affected by the top coding procedure applied to the CPS by the Census Bureau and the Bureau of Labor Statistics.

8 Summary and conclusions

This paper analyzes the role of occupational segregation in explaining the decline in female chances of working in a highly remunerated position over the life-cycle. In summary, it aims to answer the following questions: given workers with identical observable characteristics, what is the differential probability that women earn remunerations located above certain threshold in relation to their men counterparts? and how much of this relative probability is explained by occupational segregation as workers age?

The empirical approach used to answer these goals is a two-step decomposition technique. Contrary to the standard Oaxaca-Blinder method, this approach performs a conditional decomposition by partitioning the coefficient associated with a female indicator in a linear probability equation into occupational segregation and within-occupation gender inequality.

The most remarkable finding is that the contribution of the gender occupational segregation to the decline in the female chances of working in a highly remunerated position over the life course is zero for most of the wage distribution. However, the importance of the occupational segregation in explaining the lower female chances of earning wages located at the top dramatically increases as workers age. These results suggest the presence of a gender 'glass ceiling'.

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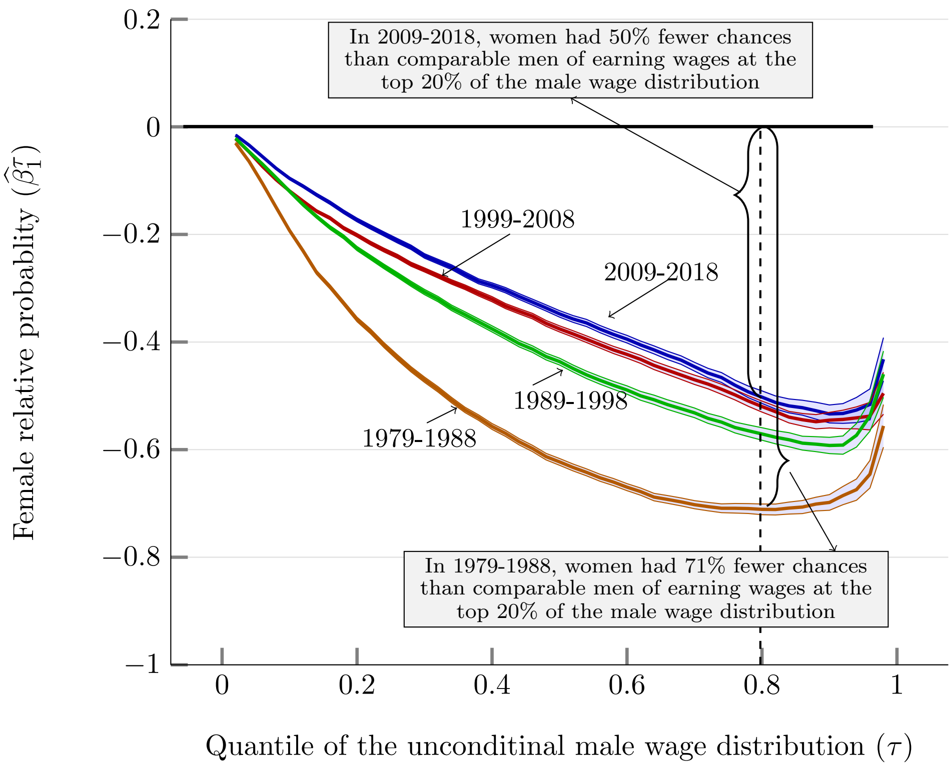
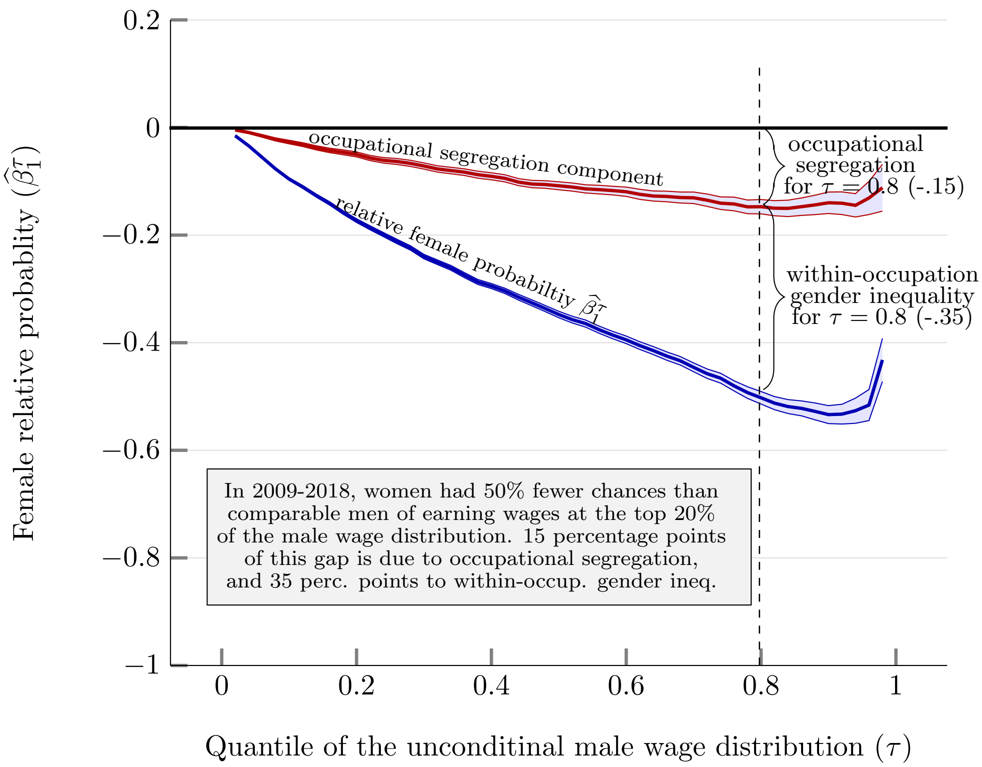
9 Figures

Figure 2: Women's relative probability of earning more than given quantile
(all workers 25-64 years old)



Note: Shadow regions around curves are bootstrapped 95% confidence bands (200 rep). The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions (4) used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range.

Figure 3: Decomposing the women's relative probability of earning more than given quantile (all workers 25-64 years old - period 2009-2018)



Note: Shadow regions around curves are bootstrapped 95% confidence bands (200 rep). The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions (4) used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range. Workers classified in 77 occupations (first level of aggregation CPS-1990 basis).

Figure 4: Women's relative probability of earning more than given quantile explained by occupational segregation (proportion)

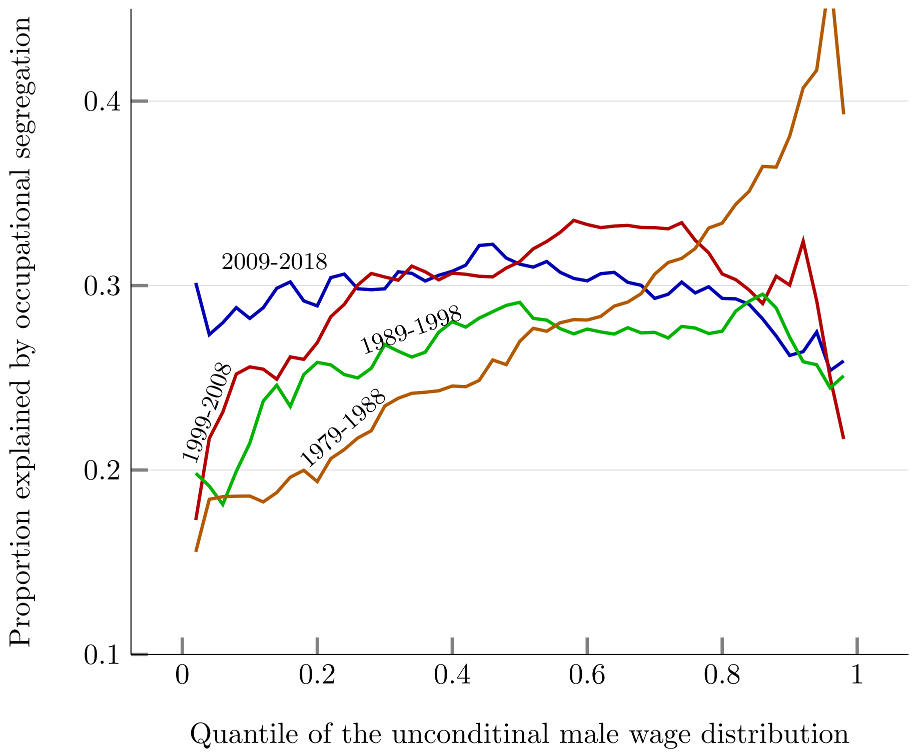


Figure 5: Decomposing the women's relative probability of earning more than given quantile (all workers 25-64 years old - multiple periods)

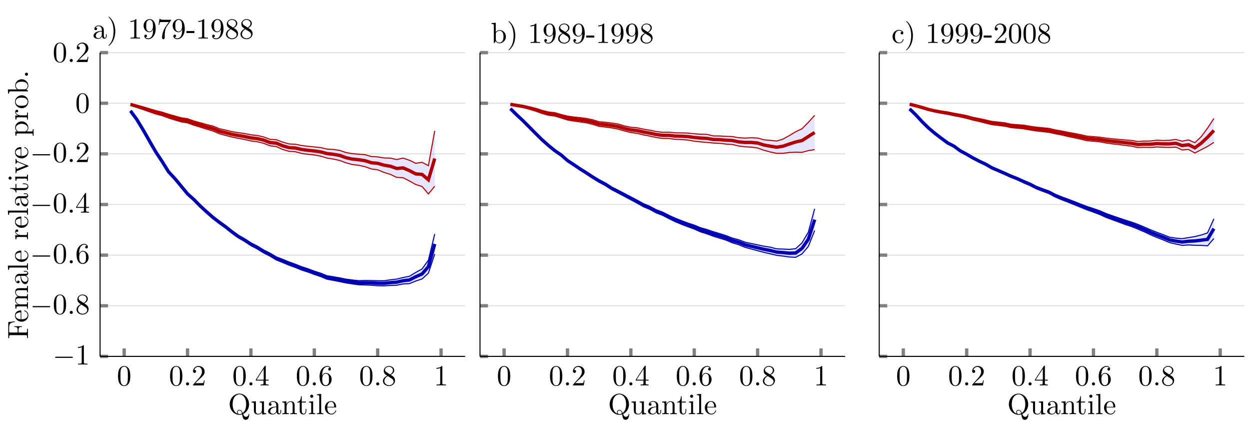
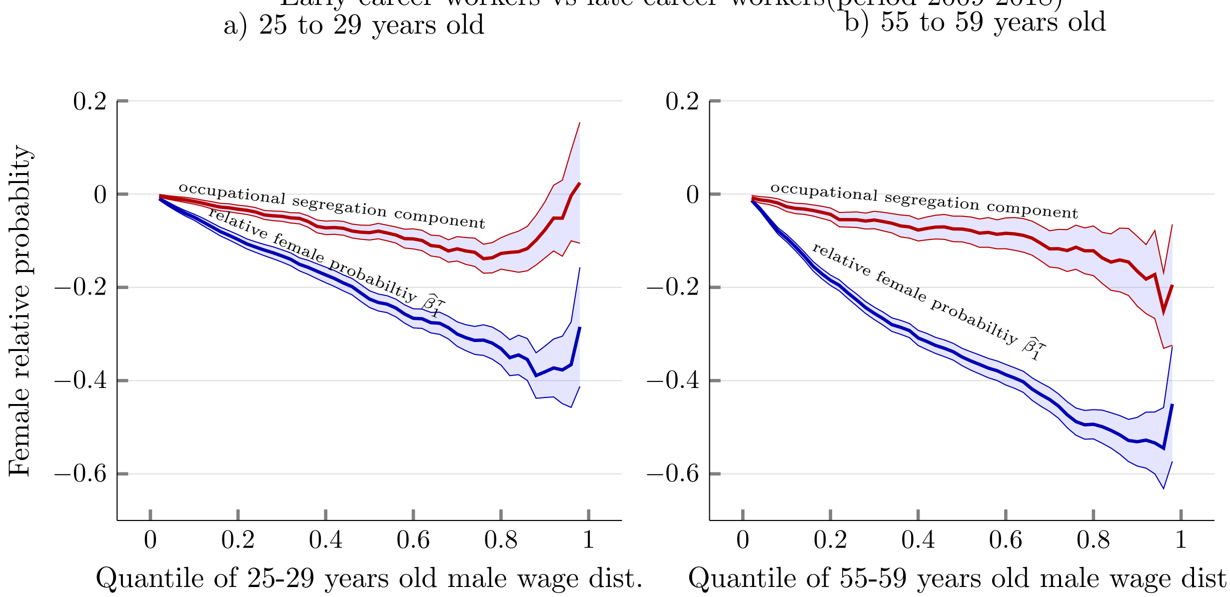
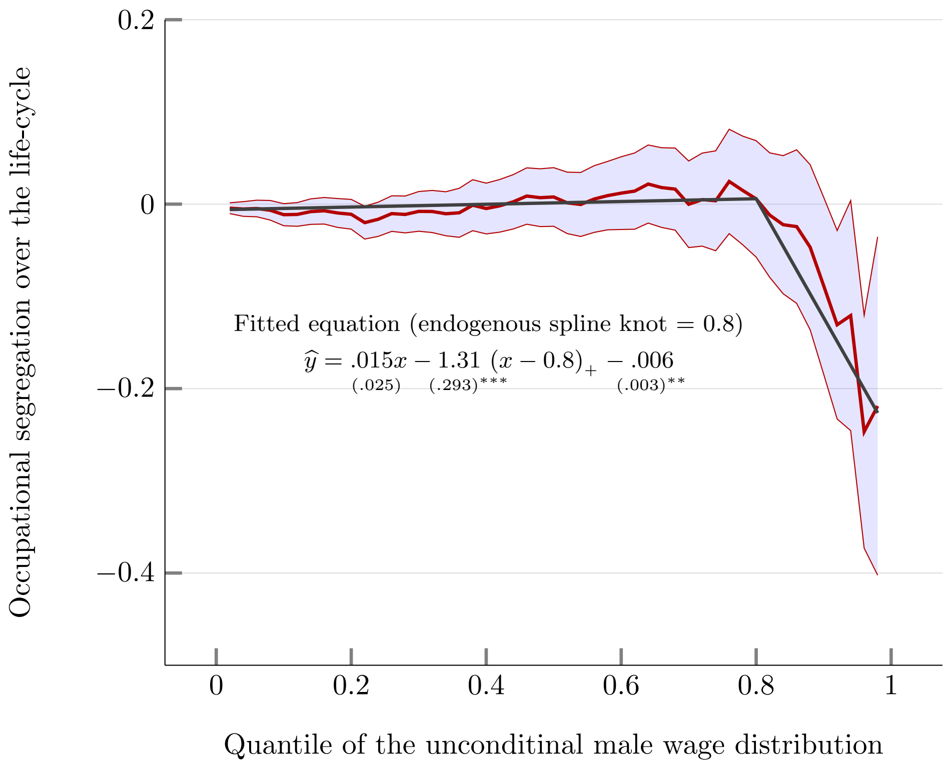


Figure 6: Decomposing women's relative probability of earning more than given quantile:
Early-career workers vs late-career workers(period 2009-2018)



Note: Shadow regions around curves are bootstrapped 95% confidence bands (200 rep). The quantiles of the unconditional male wage distribution are computed for each age group and survey year. Regressions (4) used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range.

Figure 7: Changes in occupational segregation over the life-cicle:
Late-career workers vs early-career workers (period 2009-2018)



Note: Shadow area is the bootstrapped 95% confidence bands (200 rep). The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions (4) used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range. Workers classified in 77 occupations (first level of aggregation CPS-1990 basis).

Figure 8: Life-cycle: decompositions

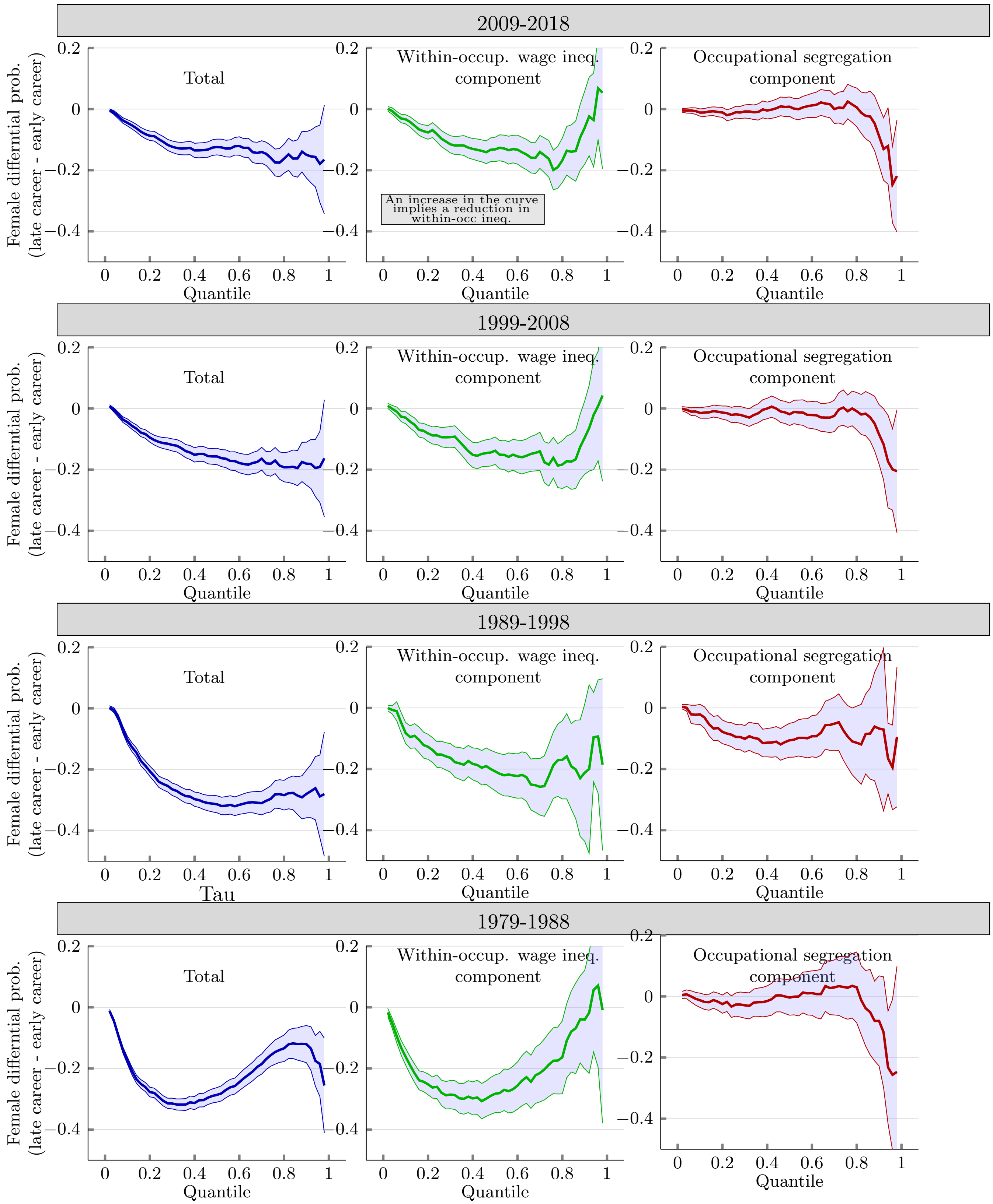


Figure 9: Changes in managerial positions segregation over the life-cycle

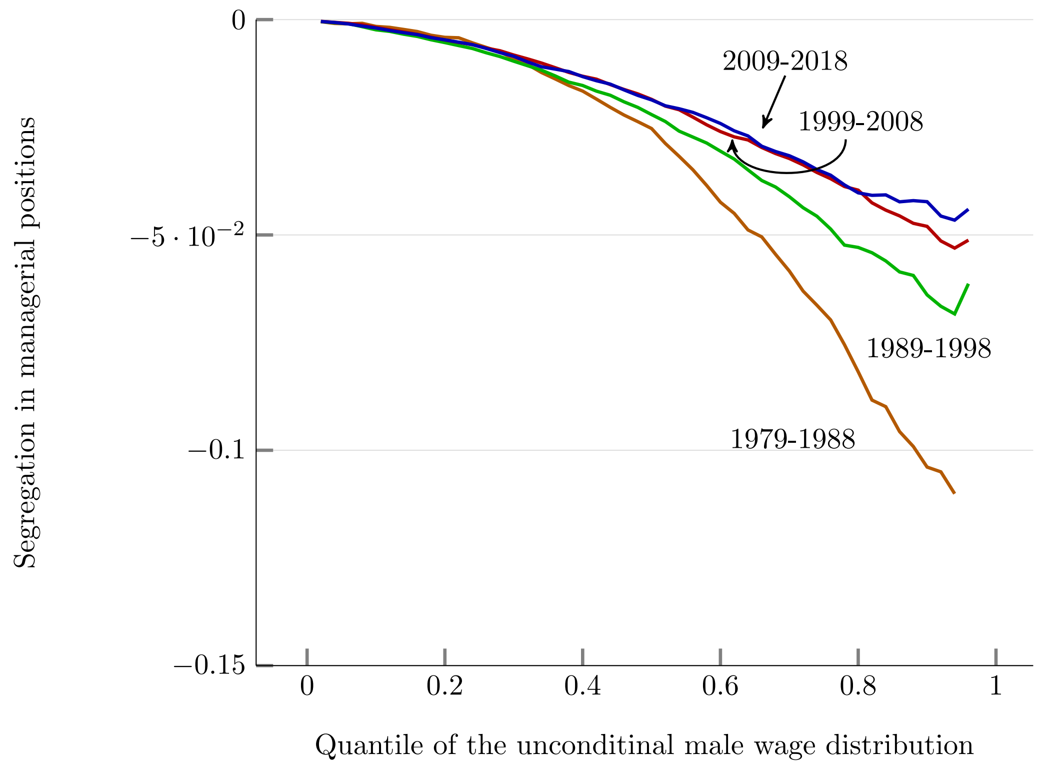


Figure 10: Occupational segregation component: women's relative probability of earning more than given quantile
(period 2009-2018)

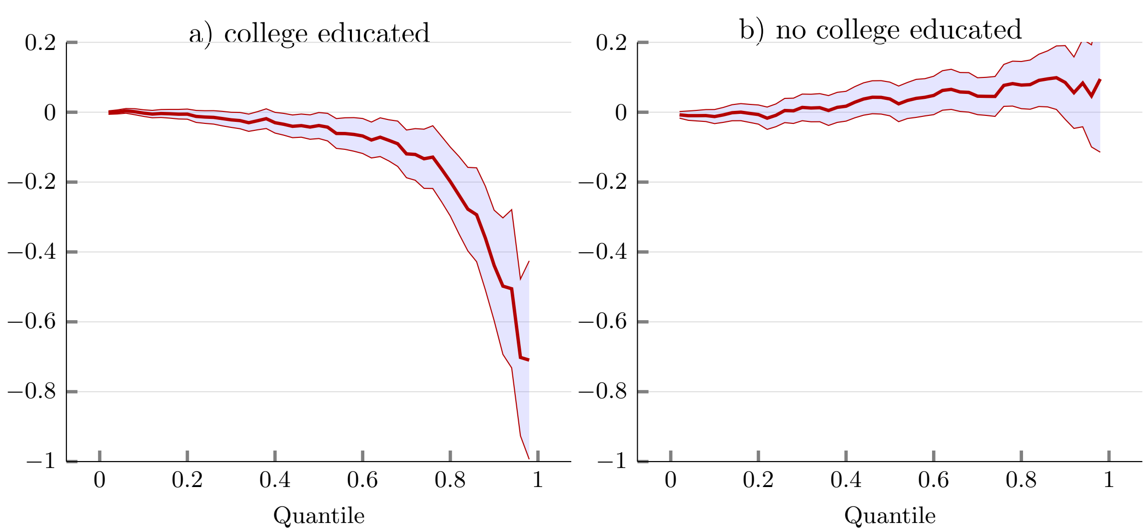
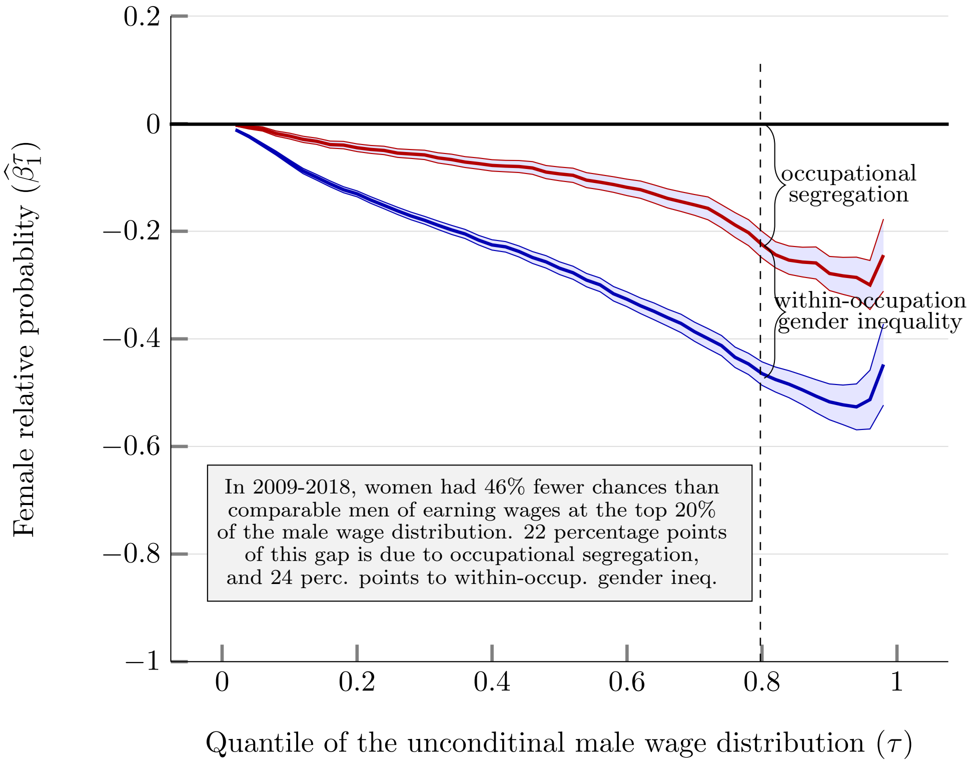
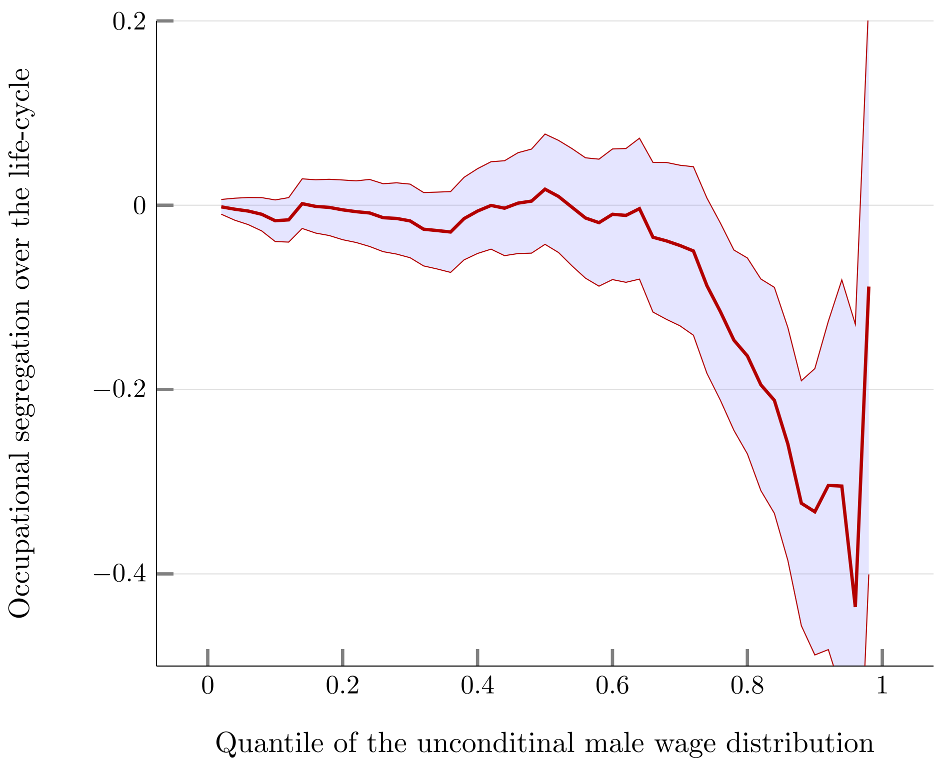


Figure 11: Decomposing women's relative probability of earning more than given quantile (occupation-industry all workers 25-64 years old - period 2011-2018)



Note: Shadow regions around curves are bootstrapped 95% confidence bands (200 rep). The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions (4) used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with a non-negative wage and/or salary income in the age range.

Figure 12: Changes in occupational segregation (narrow classification) over the life-cicle: Late-career workers vs early-career workers (period 2009-2018)



Note: Shadow regions around curves are bootstrapped 95% confidence bands (200 rep). The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions (4) used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range. Workers classified in 221 occupations (occupation-industry combination).

Appendix I

Appendix I.1: Summary statistics

Table AI.1: Summary statistics
(Workers with positive wages - 25 to 64 years old)

	1979-1988		1989-1998		1999-2008		2009-2018	
	mean	sd	mean	sd	mean	sd	mean	sd
log wage	2.461	0.928	2.489	0.853	2.620	0.855	2.632	0.865
female	0.437	0.496	0.463	0.499	0.469	0.499	0.474	0.499
age	40.2	10.8	40.4	10.0	42.2	10.3	43.3	11.0
Education								
less than high school	0.160	0.367	0.101	0.301	0.080	0.272	0.064	0.244
high school	0.399	0.490	0.358	0.479	0.310	0.463	0.272	0.445
some college	0.189	0.392	0.256	0.436	0.279	0.449	0.277	0.448
B.A. degree	0.142	0.349	0.184	0.387	0.218	0.413	0.246	0.430
More than B.A.	0.110	0.313	0.102	0.303	0.113	0.316	0.141	0.348
Race/ethnicity								
white	0.800	0.400	0.768	0.422	0.707	0.455	0.657	0.475
black	0.099	0.299	0.106	0.307	0.109	0.312	0.110	0.312
hispanic	0.056	0.230	0.081	0.273	0.121	0.326	0.150	0.357
others	0.045	0.207	0.045	0.208	0.063	0.243	0.083	0.276
observations	482,439		490,061		686,981		673,692	

Appendix I.2: Fitting a linear spline with endogenous knot

Equation (4) gives a set of estimates β_1^τ for $\tau = 0.02, 0.04, ..., 0.98$. The procedure to estimate the standard errors consists of estimating regressions for all quantiles in each bootstrap re-sampling. This approach gives an estimate for each entry of the non-diagonal variance-covariance matrix $V(\widehat{\beta}_1^\tau)$, denoted here Ω. The vector of coefficients $\widehat{\beta}_1^\tau$ is obtained by OLS. Hence, it is asymptomatically normally distributed.

$$\widehat{\beta}_1^\tau \sim N(\beta_1^\tau, \Omega) \tag{15}$$

Computing the fitted line in Figure 7 involves regressing $\widehat{\beta}_1^\tau$ on τ accounting for the fact that the dependent variable is the result of a previously estimated set of regressions. The functional form chosen is a linear spline with one not, which adjusts a linear function with a kink.

$$\widehat{\beta}_1^\tau = \theta_1 \; \tau + \theta_2 \; (\tau - knot)_+ + \theta_3 + error \tag{16}$$

where 'regressor' τ (x-axis in Figure 7) takes 49 equally spaced values from 0.02 to 0.98, and $(\tau - knot)_+$ is a variable defined as:

$$(\tau - knot)_+ = \begin{cases} \tau - knot & \text{if } \tau > knot \\ 0 & \text{if } \tau \leq knot \end{cases}$$

Let Z be a 49×3 matrix containing the independent variables in regression (16), i.e., τ in the first column, $(\tau - knot)_+$ in the second column, and all ones in the third column. Ordinary least squares estimates of $\Theta = [\theta_1, \theta_2, \theta_3]'$ and the asymptotic variance $V(\widehat{\Theta})$ are:

$$\widehat{\Theta}_{ols} = (Z'Z)^{-1}Z'\widehat{\beta}_1 \tag{17}$$

$$\widehat{V}(\widehat{\Theta}_{ols}) = (Z'Z)^{-1}Z'\Omega Z(Z'Z)^{-1} \tag{18}$$

Ordinary least squares does not give an efficient estimator of Θ considering that evident heteroskedasticity (in Figure 7, the confident intervals increase with τ). Then, the GLS estimator is used instead.

$$\widehat{\Theta}_{gls} = (Z'\Omega^{-1}Z)^{-1}Z'\Omega^{-1}\widehat{\beta}_1 \tag{19}$$

$$\widehat{V}(\widehat{\Theta}_{gls}) = (Z'\Omega^{-1}Z)^{-1} \tag{20}$$

Finding the optimal *knot* The computation of the linear spline (16) requires the researcher to specify a value for the *knot* (or kink in the fitted line). Here, the optimal knot is obtained by estimating (16) multiple times varying the value of the knot from 0.04 to 0.96 in 0.02 increments (there has to be at least one observation on each side of the knot) and then choose the knot that maximizes the R^2.

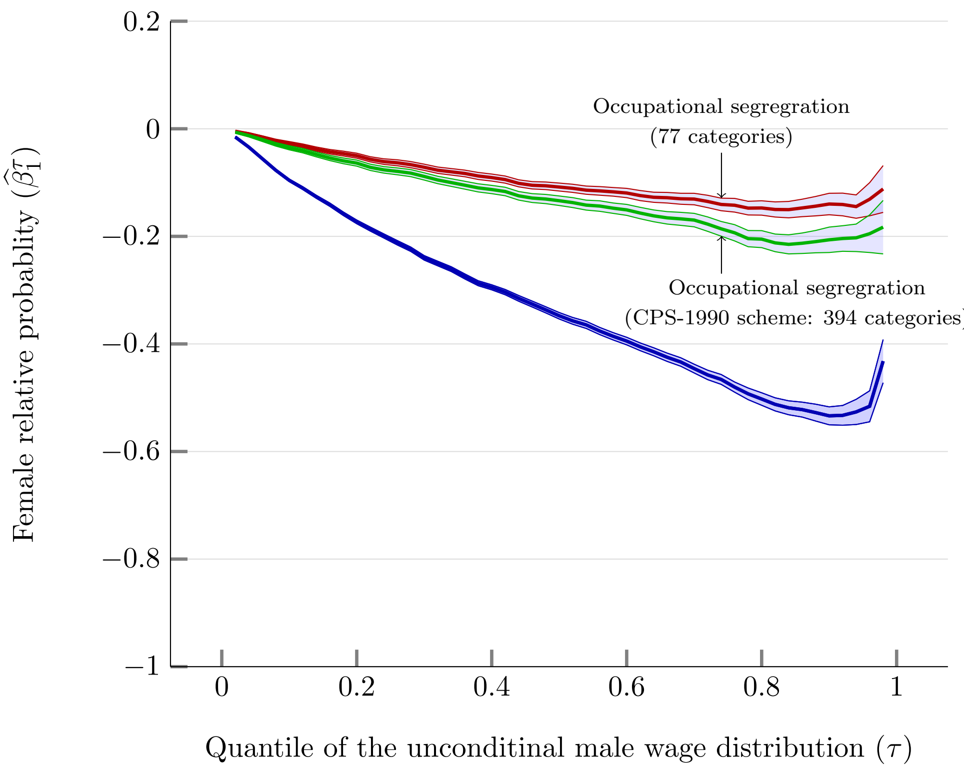
Appendix II: Robustness analyses

This Appendix shows robustness results in relation to the classification of occupations used and the definition of 'early-career' 'late-career' workers.

AII.1 Alternative classification of occupations

Figure A.1 is replica of Figure 2 in text with the caveat that in addition to performing the decomposition using 77 occupations, it also shows the decomposition using the original 394 occupational categories 1990-basis scheme included in the CPS. The aggregation procedure used to make the classification consistent over the years affects little the results.

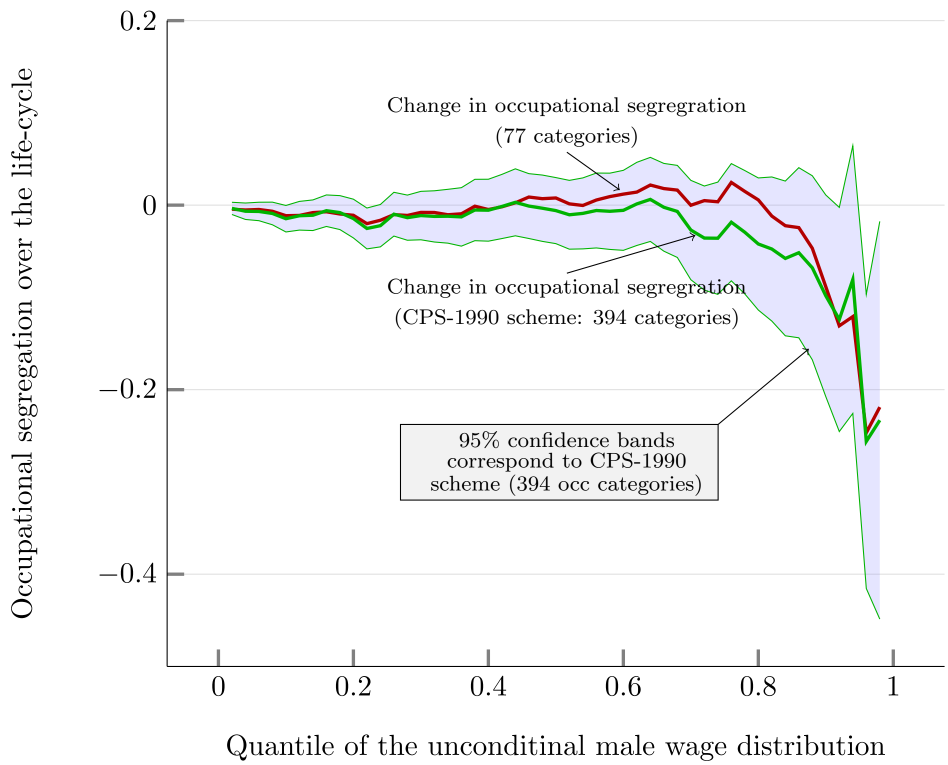
Figure A.1: Decomposing the women's relative probability of earning more than given quantile: Alternative classifications of occupations (all workers 25-64 years old - period 2009-2018)



Note: Shadow regions around curves are bootstrapped 95% confidence bands (200 rep). The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range. Workers classified in 77 occupations (first level of aggregation CPS-1990 basis, see appendix) and in the original 394 occupations CPS-1990 basis.

Figure A.2 is replica of Figure 6 in text with the caveat that in addition to performing the decomposition using 77 occupations, it also shows the decomposition using the original 394 occupational categories 1990-basis scheme included in the CPS. As in the previous case, the aggregation procedure used to make the classification consistent over the years affects the results in a non-significant way. The 95% confidence bands computed for the 394 occupational scheme contain the point estimate when the aggregated 77 occupational scheme is used.

Figure A.2: Changes in occupational segregation over the life-cicle:
Late-career workers vs early-career workers (period 2009-2018)
Alternative classifications of occupations

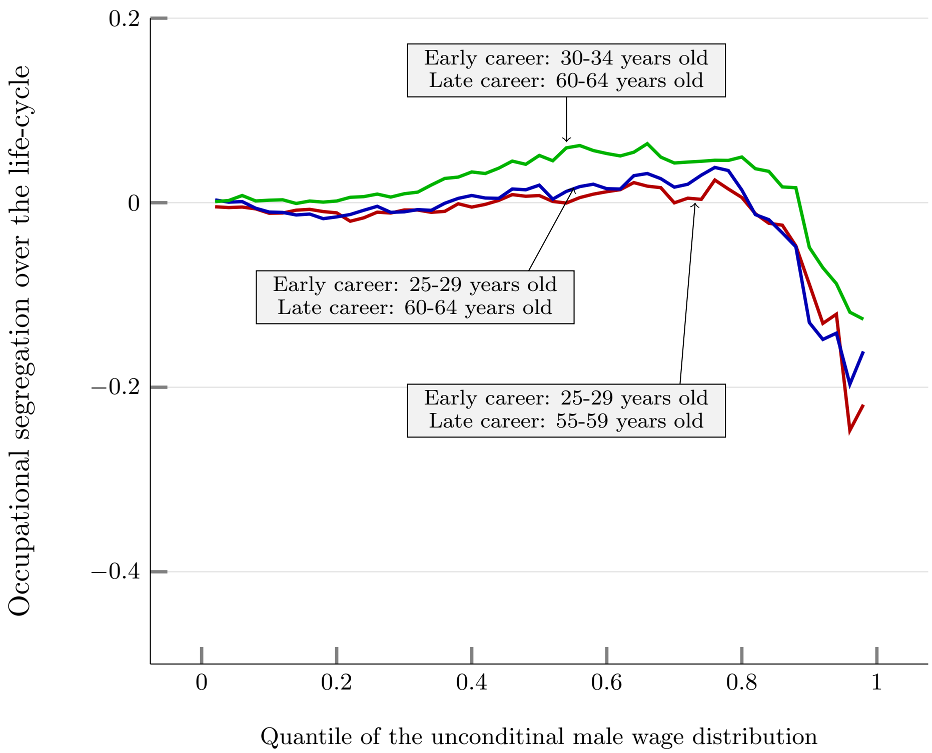


Note: Shadow regions around curves are bootstrapped 95% confidence bands (200 rep) when the original CPS-1990 occupational scheme is used. The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range. Workers classified in 77 occupations (first level of aggregation CPS-1990 basis, see appendix) and in the original 394 occupations CPS-1990 basis.

AII.2 Alternative definitions of 'early-career' and 'late-career' workers

In the main text, 'early-career' workers were defined as worker who are 25 to 29 year old and 'late-career' as workers who are 55 to 59 years old. Figure A.3 replicates Figure 6 in text with alternative definitions of 'early-career' and 'late-career' workers. The main conclusions are invariant to the definition used. The occupational segregation component is unchanged over the life-cycle for most of the wage distribution except for job positions located at the top.

Figure A.3: Changes in occupational segregation over the life-cicle:
Late-career workers vs early-career workers (period 2009-2018)
Alternative age groups



Note: The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range. Workers classified in 77 occupations (first level of aggregation CPS-1990 basis, see appendix).

AII.3 Top coding

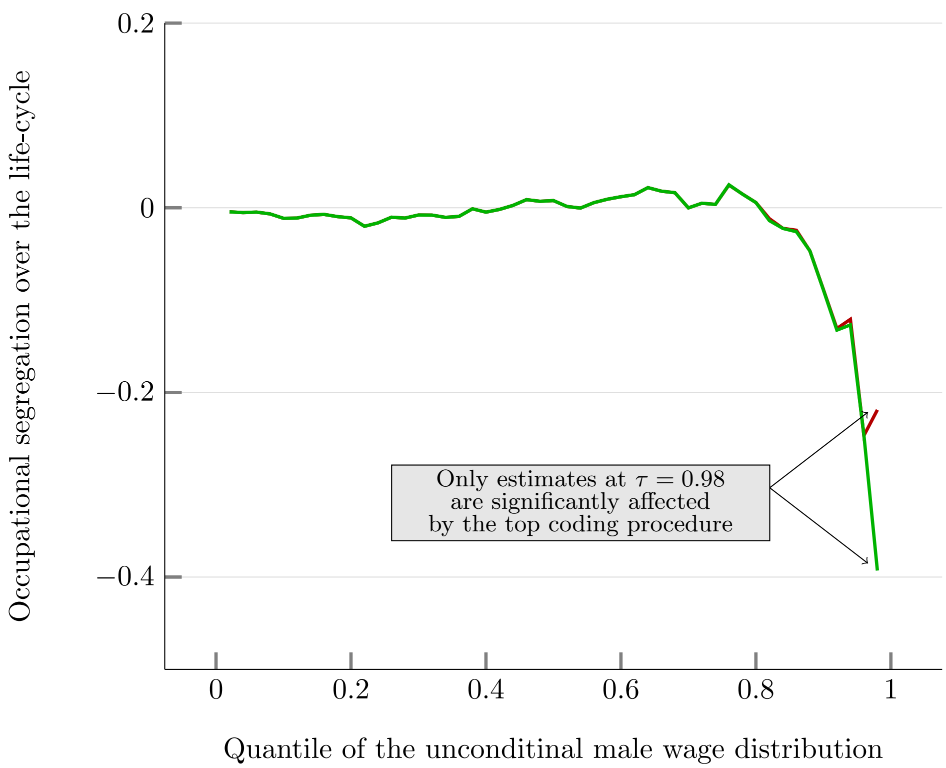
The CPS data provide income information after a top coding procedure is applied. Earnings of highly-remunerated workers are replaced to preserve the anonymity.

The top coding rules have changed over the years. The risk for the technique implemented in this paper is that highly-remunerated worker are misclassified as not being such. In principle, there should be no concern since the top coding procedure affect the top 1% of the population. So, even when the regression use the quantile 0.98 to classify highly-paid individuals, which is the maximum computed, the top coding should no affect the results. Nonetheless, the top coding procedure contemplates earnings, not hourly wages as in this paper.

Figure A.4 shows the result of adjusting top coded workers wages. If an individual is identified as being subject to top coding, his/her wage is replaced by the maximum wage observed in the dataset. Then, he/she will be classified as a highly-remunerated individual irrespectively of the quantile used as a threshold. This procedure puts a bound on the error derived from top coding.

Results in Figure A.4. show that only one point in the curve ($\tau = 0.8$) is significantly affected by the top coding procedure.

Figure A.4: Changes in occupational segregation over the life-cicle:
Top coding robustness (period 2009-2018)



Note: The robustness procedure consists of replacing the wage of the top coded workers by the maximum observed in the distribution. The quantiles of the unconditional male wage distribution are computed for each survey year. Regressions used to compute each curve include age, dummies for education - less than high school, high school completion (omitted category), some college, B.A. degree, more than B.A. degree - and race/ethnicity indicators - non-hispanic whites (omitted category), blacks, hispanics and 'others'. The sample includes all individuals with non-negative labor income in the age range. Workers classified in 77 occupations (first level of aggregation CPS-1990 basis).

Appendix III: A narrow classification of occupations

This table shows the narrowest possible classification of occupations in the data (named for convenience 'job types' here). They are defined as a combination of industries and occupations with at least ten female workers and ten male worker per year in each cell. The pooling of dataset over the years results in more than a hundred workers of each sex per 'job type'.

Job types (industry-occupation combinations)

Each line represents a 'job' defined as an occupation-industry cell with at least 10 workers per sex in each year from 2011 to 2018, (#Jobs=221)

Ind. code	Occup. code	Industry (CPS 1990-basis scheme)	Occupation (CPS 2010-basis scheme)
10	205	Agricultural production, crops	Farmers, Ranchers, and Other Agricultural Managers
10	6050	Agricultural production, crops	Agricultural workers, nec
11	205	Agricultural production, livestock	Farmers, Ranchers, and Other Agricultural Managers
11	6050	Agricultural production, livestock	Agricultural workers, nec
12	3250	Veterinary services	Veterinarians
20	4250	Landscape and horticultural services	Grounds Maintenance Workers
60	220	All construction	Constructions Managers
60	430	All construction	Managers, nec (including Postmasters)
60	6260	All construction	Construction Laborers
60	6420	All construction	Painters, Construction and Maintenance
60	7220	All construction	Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics
100	7810	Meat products	Butchers and Other Meat, Poultry, and Fish Processing Workers
100	8800	Meat products	Packaging and Filling Machine Operators and Tenders
171	2810	Newspaper publishing and printing	Editors, News Analysts, Reporters, and Correspondents
172	430	Printing, publishing, and allied industries, except newspapers	Managers, nec (including Postmasters)
172	8230	Printing, publishing, and allied industries, except newspapers	Bookbinders, Printing Machine Operators, and Job Printers
342	7720	Electrical machinery, equipment, and supplies, n.e.c.	Electrical, Electronics, and Electromechanical Assemblers
351	7750	Motor vehicles and motor vehicle equipment	Assemblers and Fabricators, nec
391	8965	Miscellaneous manufacturing industries	Other production workers including semiconductor processors and cooling and freezing equipment operators
401	9100	Bus service and urban transit	Bus and Ambulance Drivers and Attendants
402	9140	Taxicab service	Taxi Drivers and Chauffeurs
410	5520	Trucking service	Dispatchers
410	7210	Trucking service	Bus and Truck Mechanics and Diesel Engine Specialists
410	9130	Trucking service	Driver/Sales Workers and Truck Drivers
410	9620	Trucking service	Laborers and Freight, Stock, and Material Movers, Hand
412	5540	U.S. Postal Service	Postal Service Clerks
412	5550	U.S. Postal Service	Postal Service Mail Carriers
412	5560	U.S. Postal Service	Postal Service Mail Sorters, Processors, and Processing Machine Operators
432	430	Services incidental to transportation	Managers, nec (including Postmasters)
510	4850	Professional and commercial equipment and supplies	Sales Representatives, Wholesale and Manufacturing
541	4850	Drugs, chemicals, and allied products	Sales Representatives, Wholesale and Manufacturing
550	4850	Groceries and related products	Sales Representatives, Wholesale and Manufacturing
580	4700	Lumber and building material retailing	First-Line Supervisors of Sales Workers
580	4760	Lumber and building material retailing	Retail Salespersons
580	5240	Lumber and building material retailing	Customer Service Representatives
591	4700	Department stores	First-Line Supervisors of Sales Workers
591	4720	Department stores	Cashiers
591	4760	Department stores	Retail Salespersons
591	5240	Department stores	Customer Service Representatives
591	5620	Department stores	Stock Clerks and Order Fillers
600	4700	Miscellaneous general merchandise stores	First-Line Supervisors of Sales Workers
600	5620	Miscellaneous general merchandise stores	Stock Clerks and Order Fillers
601	4000	Grocery stores	Chefs and Cooks
601	4030	Grocery stores	Food Preparation Workers
601	4050	Grocery stores	Combined Food Preparation and Serving Workers, Including Fast Food
601	4700	Grocery stores	First-Line Supervisors of Sales Workers
601	4720	Grocery stores	Cashiers
601	5240	Grocery stores	Customer Service Representatives
601	5620	Grocery stores	Stock Clerks and Order Fillers
601	9620	Grocery stores	Laborers and Freight, Stock, and Material Movers, Hand
610	7800	Retail bakeries	Bakers
611	4700	Food stores, n.e.c.	First-Line Supervisors of Sales Workers
612	4760	Motor vehicle dealers	Retail Salespersons
620	7200	Auto and home supply stores	Automotive Service Technicians and Mechanics
620	7260	Auto and home supply stores	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers, nec

Continued on next page

Table 1 – *Continued from previous page*

Ind. code	Occup. code	Industry (CPS 1990-basis scheme)	Occupation (CPS 2010-basis scheme)
621	4700	Gasoline service stations	First-Line Supervisors of Sales Workers
621	4720	Gasoline service stations	Cashiers
623	4700	Apparel and accessory stores, except shoe	First-Line Supervisors of Sales Workers
623	4760	Apparel and accessory stores, except shoe	Retail Salespersons
630	4760	Shoe stores	Retail Salespersons
631	4700	Furniture and home furnishings stores	First-Line Supervisors of Sales Workers
631	4760	Furniture and home furnishings stores	Retail Salespersons
633	4700	Radio, TV, and computer stores	First-Line Supervisors of Sales Workers
633	4760	Radio, TV, and computer stores	Retail Salespersons
641	20	Eating and drinking places	General and Operations Managers
641	310	Eating and drinking places	Food Service and Lodging Managers
641	4000	Eating and drinking places	Chefs and Cooks
641	4010	Eating and drinking places	First-Line Supervisors of Food Preparation and Serving Workers
641	4030	Eating and drinking places	Food Preparation Workers
641	4040	Eating and drinking places	Bartenders
641	4050	Eating and drinking places	Combined Food Preparation and Serving Workers, Including Fast Food
641	4060	Eating and drinking places	Counter Attendant, Cafeteria, Food Concession, and Coffee Shop
641	4110	Eating and drinking places	Waiters and Waitresses
641	4130	Eating and drinking places	Food preparation and serving related workers, nec
641	4140	Eating and drinking places	Dishwashers
641	4150	Eating and drinking places	Host and Hostesses, Restaurant, Lounge, and Coffee Shop
641	4220	Eating and drinking places	Janitors and Building Cleaners
641	4720	Eating and drinking places	Cashiers
641	5240	Eating and drinking places	Customer Service Representatives
641	9130	Eating and drinking places	Driver/Sales Workers and Truck Drivers
642	3050	Drug stores	Pharmacists
642	3410	Drug stores	Health Diagnosing and Treating Practitioner Support Technicians
642	4700	Drug stores	First-Line Supervisors of Sales Workers
642	4720	Drug stores	Cashiers
642	4760	Drug stores	Retail Salespersons
650	4720	Liquor stores	Cashiers
651	4700	Sporting goods, bicycles, and hobby stores	First-Line Supervisors of Sales Workers
651	4760	Sporting goods, bicycles, and hobby stores	Retail Salespersons
652	4700	Book and stationery stores	First-Line Supervisors of Sales Workers
652	4760	Book and stationery stores	Retail Salespersons
660	4700	Jewelry stores	First-Line Supervisors of Sales Workers
671	4950	Direct selling establishments	Door-to-Door Sales Workers, News and Street Vendors, and Related Workers
672	9130	Fuel dealers	Driver/Sales Workers and Truck Drivers
682	4700	Miscellaneous retail stores	First-Line Supervisors of Sales Workers
682	4760	Miscellaneous retail stores	Retail Salespersons
691	4700	Retail trade, n.s.	First-Line Supervisors of Sales Workers
691	4760	Retail trade, n.s.	Retail Salespersons
700	10	Banking	Chief executives and legislators/public administration
700	120	Banking	Financial Managers
700	910	Banking	Credit Counselors and Loan Officers
700	5160	Banking	Bank Tellers
700	5240	Banking	Customer Service Representatives
702	120	Credit agencies, n.e.c.	Financial Managers
702	910	Credit agencies, n.e.c.	Credit Counselors and Loan Officers
710	120	Security, commodity brokerage, and investment companies	Financial Managers
710	520	Security, commodity brokerage, and investment companies	Wholesale and Retail Buyers, Except Farm Products
710	850	Security, commodity brokerage, and investment companies	Personal Financial Advisors
710	4820	Security, commodity brokerage, and investment companies	Securities, Commodities, and Financial Services Sales Agents
711	430	Insurance	Managers, nec (including Postmasters)
711	540	Insurance	Claims Adjusters, Appraisers, Examiners, and Investigators
711	860	Insurance	Insurance Underwriters
711	4700	Insurance	First-Line Supervisors of Sales Workers
711	4810	Insurance	Insurance Sales Agents
711	5840	Insurance	Insurance Claims and Policy Processing Clerks
712	410	Real estate, including real estate-insurance offices	Property, Real Estate, and Community Association Managers
712	4920	Real estate, including real estate-insurance offices	Real Estate Brokers and Sales Agents
721	30	Advertising	Managers in Marketing, Advertising, and Public Relations
721	4800	Advertising	Advertising Sales Agents
722	4200	Services to dwellings and other buildings	First-Line Supervisors of Housekeeping and Janitorial Workers
722	4220	Services to dwellings and other buildings	Janitors and Building Cleaners
722	4230	Services to dwellings and other buildings	Maids and Housekeeping Cleaners
731	430	Personnel supply services	Managers, nec (including Postmasters)
731	620	Personnel supply services	Human Resources, Training, and Labor Relations Specialists
732	110	Computer and data processing services	Computer and Information Systems Managers
732	430	Computer and data processing services	Managers, nec (including Postmasters)
732	1000	Computer and data processing services	Computer Scientists and Systems Analysts/Network systems Analysts/Web Developers
732	1010	Computer and data processing services	Computer Programmers

Continued on next page

Table 1 – *Continued from previous page*

Ind. code	Occup. code	Industry (CPS 1990-basis scheme)	Occupation (CPS 2010-basis scheme)
732	1020	Computer and data processing services	Software Developers, Applications and Systems Software
732	1050	Computer and data processing services	Computer Support Specialists
732	4840	Computer and data processing services	Sales Representatives, Services, All Other
740	3930	Detective and protective services	Security Guards and Gaming Surveillance Officers
741	430	Business services, n.e.c.	Managers, nec (including Postmasters)
741	2630	Business services, n.e.c.	Designers
741	2910	Business services, n.e.c.	Photographers
741	5240	Business services, n.e.c.	Customer Service Representatives
762	310	Hotels and motels	Food Service and Lodging Managers
762	4000	Hotels and motels	Chefs and Cooks
762	4110	Hotels and motels	Waiters and Waitresses
762	4230	Hotels and motels	Maids and Housekeeping Cleaners
762	5300	Hotels and motels	Hotel, Motel, and Resort Desk Clerks
771	8300	Laundry, cleaning, and garment services	Laundry and Dry-Cleaning Workers
772	4510	Beauty shops	Hairdressers, Hairstylists, and Cosmetologists
791	4520	Miscellaneous personal services	Personal Appearance Workers, nec
810	2600	Miscellaneous entertainment and recreation services	Artists and Related Workers
810	2720	Miscellaneous entertainment and recreation services	Athletes, Coaches, Umpires, and Related Workers
810	2750	Miscellaneous entertainment and recreation services	Musicians, Singers, and Related Workers
810	2850	Miscellaneous entertainment and recreation services	Writers and Authors
810	3950	Miscellaneous entertainment and recreation services	Law enforcement workers, nec
810	4220	Miscellaneous entertainment and recreation services	Janitors and Building Cleaners
810	4300	Miscellaneous entertainment and recreation services	First-Line Supervisors of Gaming Workers
810	4400	Miscellaneous entertainment and recreation services	Gaming Services Workers
810	4430	Miscellaneous entertainment and recreation services	Entertainment Attendants and Related Workers, nec
810	4620	Miscellaneous entertainment and recreation services	Recreation and Fitness Workers
810	4720	Miscellaneous entertainment and recreation services	Cashiers
812	3060	Offices and clinics of physicians	Physicians and Surgeons
820	3010	Offices and clinics of dentists	Dentists
830	1820	Offices and clinics of health practitioners, n.e.c.	Psychologists
831	350	Hospitals	Medical and Health Services Managers
831	3050	Hospitals	Pharmacists
831	3060	Hospitals	Physicians and Surgeons
831	3130	Hospitals	Registered Nurses
831	3300	Hospitals	Clinical Laboratory Technologists and Technicians
831	3320	Hospitals	Diagnostic Related Technologists and Technicians
831	3410	Hospitals	Health Diagnosing and Treating Practitioner Support Technicians
831	3600	Hospitals	Nursing, Psychiatric, and Home Health Aides
831	3650	Hospitals	Medical Assistants and Other Healthcare Support Occupations, nec
831	4230	Hospitals	Maids and Housekeeping Cleaners
832	3600	Nursing and personal care facilities	Nursing, Psychiatric, and Home Health Aides
840	350	Health services, n.e.c.	Medical and Health Services Managers
840	2000	Health services, n.e.c.	Counselors
840	3060	Health services, n.e.c.	Physicians and Surgeons
840	3130	Health services, n.e.c.	Registered Nurses
840	3160	Health services, n.e.c.	Physical Therapists
840	3300	Health services, n.e.c.	Clinical Laboratory Technologists and Technicians
840	3400	Health services, n.e.c.	Emergency Medical Technicians and Paramedics
840	3600	Health services, n.e.c.	Nursing, Psychiatric, and Home Health Aides
840	3650	Health services, n.e.c.	Medical Assistants and Other Healthcare Support Occupations, nec
840	4610	Health services, n.e.c.	Personal Care Aides
841	2100	Legal services	Lawyers, and judges, magistrates, and other judicial workers
841	2140	Legal services	Paralegals and Legal Assistants
842	230	Elementary and secondary schools	Education Administrators
842	2000	Elementary and secondary schools	Counselors
842	2310	Elementary and secondary schools	Elementary and Middle School Teachers
842	2320	Elementary and secondary schools	Secondary School Teachers
842	2330	Elementary and secondary schools	Special Education Teachers
842	2540	Elementary and secondary schools	Teacher Assistants
842	4220	Elementary and secondary schools	Janitors and Building Cleaners
842	9100	Elementary and secondary schools	Bus and Ambulance Drivers and Attendants
850	230	Colleges and universities	Education Administrators
850	2000	Colleges and universities	Counselors
850	2200	Colleges and universities	Postsecondary Teachers
850	4220	Colleges and universities	Janitors and Building Cleaners
860	2340	Educational services, n.e.c.	Other Teachers and Instructors
860	2720	Educational services, n.e.c.	Athletes, Coaches, Umpires, and Related Workers
862	4600	Child day care services	Childcare Workers
870	4610	Residential care facilities, without nursing	Personal Care Aides
871	420	Social services, n.e.c.	Social and Community Service Managers
871	2000	Social services, n.e.c.	Counselors
871	2010	Social services, n.e.c.	Social Workers
871	4610	Social services, n.e.c.	Personal Care Aides

Continued on next page

Table 1 – *Continued from previous page*

Ind. code	Occup. code	Industry (CPS 1990-basis scheme)	Occupation (CPS 2010-basis scheme)
880	2040	Religious organizations	Clergy
880	4220	Religious organizations	Janitors and Building Cleaners
881	420	Membership organizations, n.e.c.	Social and Community Service Managers
882	430	Engineering, architectural, and surveying services	Managers, nec (including Postmasters)
882	1300	Engineering, architectural, and surveying services	Architects, Except Naval
882	1360	Engineering, architectural, and surveying services	Civil Engineers
890	430	Accounting, auditing, and bookkeeping services	Managers, nec (including Postmasters)
890	800	Accounting, auditing, and bookkeeping services	Accountants and Auditors
890	940	Accounting, auditing, and bookkeeping services	Tax Preparers
891	430	Research, development, and testing services	Managers, nec (including Postmasters)
892	10	Management and public relations services	Chief executives and legislators/public administration
892	430	Management and public relations services	Managers, nec (including Postmasters)
892	710	Management and public relations services	Management Analysts
900	430	Executive and legislative offices	Managers, nec (including Postmasters)
910	2010	Justice, public order, and safety	Social Workers
910	2100	Justice, public order, and safety	Lawyers, and judges, magistrates, and other judicial workers
910	3800	Justice, public order, and safety	Sheriffs, Bailiffs, Correctional Officers, and Jailers
910	3820	Justice, public order, and safety	Police Officers and Detectives
910	5520	Justice, public order, and safety	Dispatchers
922	430	Administration of human resources programs	Managers, nec (including Postmasters)
932	430	National security and international affairs	Managers, nec (including Postmasters)

Appendix IV: Classification of occupations (consistent aggregation)

This table shows the original classification of occupations (CPS-1990 basis scheme) and the aggregation used to make the occupations consistent over time. The resulting 77 groups are used to measure occupational segregation.

Aggregation of occupations used in the analysis

Occupations (CPS classification scheme - 1990 basis)	**CPS code (#occup.=394)**	**Aggregation (#occup.=77)**
MANAGERIAL AND PROFESSIONAL SPECIALTY OCCUPATIONS		
Executive, Administrative, and Managerial Occupations:		
Legislators	3	1
Chief executives and public administrators	4	1
Financial Managers	7	1
Human resources and labor relations managers	8	1
Managers and specialists in marketing, advertising, and public relations	13	1
Managers in education and related fields	14	1
Managers of medicine and health occupations	15	1
Postmasters and mail superintendents	16	1
Managers of food-serving and lodging establishments	17	1
Managers of properties and real estate	18	1
Funeral directors	19	1
Managers of service organizations, n.e.c.	21	1
Managers and administrators, n.e.c.	22	1
Management Related Occupations:		
Accountants and auditors	23	2
Insurance underwriters	24	2
Other financial specialists	25	2
Management analysts	26	2
Personnel, HR, training, and labor relations specialists	27	2
Purchasing agents and buyers, of farm products	28	2
Buyers, wholesale and retail trade	29	2
Purchasing managers, agents and buyers, n.e.c.	33	2
Business and promotion agents	34	2
Construction inspectors	35	2
Inspectors and compliance officers, outside construction	36	2
Management support occupations	37	2
Professional Specialty Occupations		
Engineers, Architechts, and Surveyors:		
Architects	43	3
Engineers:		
Aerospace engineer	44	4
Metallurgical and materials engineers, variously phrased	45	4
Petroleum, mining, and geological engineers	47	4
Chemical engineers	48	4
Civil engineers	53	4
Electrical engineer	55	4
Industrial engineers	56	4
Mechanical engineers	57	4
Not-elsewhere-classified engineers	59	4
Mathematical and Computer Scientists:		
Computer systems analysts and computer scientists	64	5
Operations and systems researchers and analysts	65	5

Continued on next page

Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Actuaries	66	5
Statisticians	67	5
Mathematicians and mathematical scientists	68	5
Natural Scientists:		
Physicists and astronomers	69	6
Chemists	73	6
Atmospheric and space scientists	74	6
Geologists	75	6
Physical scientists, n.e.c.	76	6
Agricultural and food scientists	77	6
Biological scientists	78	6
Foresters and conservation scientists	79	6
Medical scientists	83	6
Health Diagnosing Occupations:		
Physicians	84	7
Dentists	85	7
Veterinarians	86	7
Optometrists	87	7
Podiatrists	88	7
Other health and therapy	89	7
Health Assessment and Treating Occupations:		
Registered nurses	95	8
Pharmacists	96	8
Dietitians and nutritionists	97	8
Therapists:		
Respiratory therapists	98	9
Occupational therapists	99	9
Physical therapists	103	9
Speech therapists	104	9
Therapists, n.e.c.	105	9
Physicians' assistants	106	9
Teachers, Postsecondary:		
Earth, environmental, and marine science instructors	113	10
Biological science instructors	114	10
Chemistry instructors	115	10
Physics instructors	116	10
Psychology instructors	118	10
Economics instructors	119	10
History instructors	123	10
Sociology instructors	125	10
Engineering instructors	127	10
Math instructors	128	10
Education instructors	139	10
Law instructors	145	10
Theology instructors	147	10
Home economics instructors	149	10
Humanities profs/instructors, college, nec	150	10
Subject instructors (HS/college)	154	10
Teachers, Except Postsecondary:		
Kindergarten and earlier school teachers	155	11
Primary school teachers	156	11
Secondary school teachers	157	11
Special education teachers	158	11
Teachers , n.e.c.	159	11

Continued on next page

Table 1 – *Continued from previous page*

Occupations	CPS code	Aggregation
Vocational and educational counselors	163	11
Librarians, Archivists, and Curators:		
Librarians	164	12
Archivists and curators	165	12
Social Scientists and Urban Planners:		
Economists, market researchers, and survey researchers	166	13
Psychologists	167	13
Sociologists	168	13
Social scientists, n.e.c.	169	13
Urban and regional planners	173	13
Social, Recreation, and Religious Workers:		
Social workers	174	14
Recreation workers	175	14
Clergy and religious workers	176	14
Lawyers and Judges:		
Lawyers	178	15
Judges	179	15
Writers, Artists, Entertainers, and Athletes:		
Writers and authors	183	16
Technical writers	184	16
Designers	185	16
Musician or composer	186	16
Actors, directors, producers	187	16
Art makers: painters, sculptors, craft-artists, and print-makers	188	16
Photographers	189	16
Dancers	193	16
Art/entertainment performers and related	194	16
Editors and reporters	195	16
Announcers	198	16
Athletes, sports instructors, and officials	199	16
Professionals, n.e.c.	200	16
TECHNICAL, SALES, AND ADMINISTRATIVE SUPPORT OCCUPATIONS		
Technicians and Related Support Occupations		
Health Technologists and Technicians:		
Clinical laboratory technologies and technicians	203	17
Dental hygenists	204	17
Health record tech specialists	205	17
Radiologic tech specialists	206	17
Licensed practical nurses	207	17
Health technologists and technicians, n.e.c.	208	17
Technologists and Technicians, Except Health		
Engineering and Related Technologists and Technicians:		
Electrical and electronic (engineering) technicians	213	18
Engineering technicians, n.e.c.	214	18
Mechanical engineering technicians	215	18
Drafters	217	18
Surveyors, cartographers, mapping scientists and technicians	218	18
Biological technicians	223	18
Science Technicians:		
Chemical technicians	224	19
Other science technicians	225	19
Technicians, Except Health, Engineering, and Science:		
Airplane pilots and navigators	226	20
Air traffic controllers	227	20

Continued on next page

Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Broadcast equipment operators	228	20
Computer software developers	229	20
Programmers of numerically controlled machine tools	233	20
Legal assistants, paralegals, legal support, etc	234	20
Technicians, n.e.c.	235	20
Sales Occupations:		
Supervisors and proprietors of sales jobs	243	21
Sales Representatives, Finance and Business Services:		
Insurance sales occupations	253	21
Real estate sales occupations	254	21
Financial services sales occupations	255	21
Advertising and related sales jobs	256	21
Sales Representatives, Commodities:		
Sales engineers	258	22
Salespersons, n.e.c.	274	22
Retail sales clerks	275	22
Cashiers	276	22
Door-to-door sales, street sales, and news vendors	277	22
Sales Related Occupations:		
Sales demonstrators / promoters / models	283	23
Sales workers–allocated (1990 internal census)	290	23
Administrative Support Occupations, Including Clerical		
Supervisors, Administrative Support Occupations:		
Office supervisors	303	24
Computer Equipment Operators:		
Computer and peripheral equipment operators	308	24
Secretaries, Stenographers, and Typists:		
Secretaries	313	25
Stenographers	314	25
Typists	315	25
Information Clerks:		
Interviewers, enumerators, and surveyors	316	26
Hotel clerks	317	26
Transportation ticket and reservation agents	318	26
Receptionists	319	26
Information clerks, nec	323	26
Records Processing Occupations, Except Financial:		
Correspondence and order clerks	326	27
Human resources clerks, except payroll and timekeeping	328	27
Library assistants	329	27
File clerks	335	27
Records clerks	336	27
Financial Records Processing Occupations:		
Bookkeepers and accounting and auditing clerks	337	28
Payroll and timekeeping clerks	338	28
Cost and rate clerks (financial records processing)	343	28
Billing clerks and related financial records processing	344	28
Duplicating, Mail, and Other Office Machine Operators:		
Duplication machine operators / office machine operators	345	29
Mail and paper handlers	346	29
Office machine operators, n.e.c.	347	29
Communications Equipment Operators:		
Telephone operators	348	30
Other telecom operators	349	30

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Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Mail and Message Distributing Occupations:		
Postal clerks, excluding mail carriers	354	31
Mail carriers for postal service	355	31
Mail clerks, outside of post office	356	31
Messengers	357	31
Material Recording, Scheduling, and Distributing Clerks:		
Dispatchers	359	32
Inspectors, n.e.c.	361	32
Shipping and receiving clerks	364	32
Stock and inventory clerks	365	32
Meter readers	366	32
Weighers, measurers, and checkers	368	32
Material recording, scheduling, production, planning, and expediting clerks	373	32
Adjusters and Investigators:		
Insurance adjusters, examiners, and investigators	375	33
Customer service reps, investigators and adjusters, except insurance	376	33
Eligibility clerks for government programs; social welfare	377	33
Bill and account collectors	378	33
Miscellaneous Administrative Support Occupations:		
General office clerks	379	34
Bank tellers	383	34
Proofreaders	384	34
Data entry keyers	385	34
Statistical clerks	386	34
Teacher's aides	387	34
Administrative support jobs, n.e.c.	389	34
Professional, technical, and kindred workers–allocated (1990 internal census)	390	34
Clerical and kindred workers–allocated (1990 internal census)	391	34
SERVICE OCCUPATIONS		
Private Household Occupations:		
Housekeepers, maids, butlers, stewards, and lodging quarters cleaners	405	35
Private household cleaners and servants	407	35
Private household workers–allocated (1990 internal census)	408	35
Protective Service Occupations		
Supervisors, Protective Servcie Occupations:		
Supervisors of guards	415	36
Firefighting and Fire Prevention Occupations:		
Fire fighting, prevention, and inspection	417	37
Police and Detectives:		
Police, detectives, and private investigators	418	38
Other law enforcement: sheriffs, bailiffs, correctional institution officers	423	38
Guards:		
Crossing guards and bridge tenders	425	39
Guards, watchmen, doorkeepers	426	39
Protective services, n.e.c.	427	39
Service Occupations, Except Protective and Household		
Food Preparation and Serivce Occupations:		
Bartenders	434	40
Waiter/waitress	435	40
Cooks, variously defined	436	40
Food counter and fountain workers	438	40
Kitchen workers	439	40
Waiter's assistant	443	40
Misc food prep workers	444	40

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Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Health Service Occupations:		
Dental assistants	445	41
Health aides, except nursing	446	41
Nursing aides, orderlies, and attendants	447	41
Cleaning and Building Service Occupations, Except Households:		
Supervisors of cleaning and building service	448	42
Janitors	453	42
Elevator operators	454	42
Pest control occupations	455	42
Personal Service Occupations:		
Supervisors of personal service jobs, n.e.c.	456	43
Barbers	457	43
Hairdressers and cosmetologists	458	43
Recreation facility attendants	459	43
Guides	461	43
Ushers	462	43
Public transportation attendants and inspectors	463	43
Baggage porters	464	43
Welfare service aides	465	43
Child care workers	468	43
Personal service occupations, nec	469	43
FARMING, FORESTRY, AND FISHING OCCUPATIONS		
Farm Operators and Managers:		
Farmers (owners and tenants)	473	44
Horticultural specialty farmers	474	44
Farm managers, except for horticultural farms	475	44
Managers of horticultural specialty farms	476	44
Other Agricultural and Related Occupations:		
Farm Occupations, Except Managerial:		
Farm workers	479	45
Farm laborers and farm foreman–allocated (1990 internal census)	480	45
Marine life cultivation workers	483	45
Nursery farming workers	484	45
Related Agricultural Occupations:		
Supervisors of agricultural occupations	485	46
Gardeners and groundskeepers	486	46
Animal caretakers except on farms	487	46
Graders and sorters of agricultural products	488	46
Inspectors of agricultural products	489	46
Forestry and Logging Occupations:		
Timber, logging, and forestry workers	496	47
Fishers, Hunters, and Trappers:		
Fishers, hunters, and kindred	498	47
PRECISION PRODUCTION, CRAFT, AND REPAIR OCCUPATIONS		
Mechanics and Repairers:		
Supervisors of mechanics and repairers	503	48
Mechanics and Repairers, Except Supervisors		
Vehicle and Mobile Equipment Mechanics and Repairers:		
Automobile mechanics	505	49
Bus, truck, and stationary engine mechanics	507	49
Aircraft mechanics	508	49
Small engine repairers	509	49
Auto body repairers	514	49
Heavy equipment and farm equipment mechanics	516	49

Continued on next page

Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Industrial machinery repairers	518	49
Machinery maintenance occupations	519	49
Electrical and Electronic Equipment Repairers:		
Repairers of industrial electrical equipment	523	50
Repairers of data processing equipment	525	50
Repairers of household appliances and power tools	526	50
Telecom and line installers and repairers	527	50
Repairers of electrical equipment, n.e.c.	533	50
Heating, air conditioning, and refigeration mechanics	534	50
Miscellaneous Mechanics and Repairers:		
Precision makers, repairers, and smiths	535	51
Locksmiths and safe repairers	536	51
Office machine repairers and mechanics	538	51
Repairers of mechanical controls and valves	539	51
Elevator installers and repairers	543	51
Millwrights	544	51
Mechanics and repairers, n.e.c.	549	51
Construction Trades		
Supervisors, Construction Occupations:		
Supervisors of construction work	558	52
Construction Trades, Except Supervisors:		
Masons, tilers, and carpet installers	563	53
Carpenters	567	53
Drywall installers	573	53
Electricians	575	53
Electric power installers and repairers	577	53
Painters, construction and maintenance	579	53
Paperhangers	583	53
Plasterers	584	53
Plumbers, pipe fitters, and steamfitters	585	53
Concrete and cement workers	588	53
Glaziers	589	53
Insulation workers	593	53
Paving, surfacing, and tamping equipment operators	594	53
Roofers and slaters	595	53
Sheet metal duct installers	596	53
Structural metal workers	597	53
Drillers of earth	598	53
Construction trades, n.e.c.	599	53
Extractive Occupations:		
Drillers of oil wells	614	54
Explosives workers	615	54
Miners	616	54
Other mining occupations	617	54
Precision Production Occupations:		
Production supervisors or foremen	628	55
Precision Metal Working Occupations:		
Tool and die makers and die setters	634	56
Machinists	637	56
Boilermakers	643	56
Precision grinders and filers	644	56
Patternmakers and model makers	645	56
Lay-out workers	646	56
Engravers	649	56

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Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Tinsmiths, coppersmiths, and sheet metal workers	653	56
Precision Woodworking Occupations:		
Cabinetmakers and bench carpenters	657	57
Furniture and wood finishers	658	57
Other precision woodworkers	659	57
Precision Textile, Apparel, and Furnishings Machine Workers:		
Dressmakers and seamstresses	666	58
Tailors	667	58
Upholsterers	668	58
Shoe repairers	669	58
Other precision apparel and fabric workers	674	58
Precision Workers, Assorted Materials:		
Hand molders and shapers, except jewelers	675	59
Optical goods workers	677	59
Dental laboratory and medical appliance technicians	678	59
Bookbinders	679	59
Other precision and craft workers	684	59
Precision Food Production Occupations:		
Butchers and meat cutters	686	60
Bakers	687	60
Batch food makers	688	60
Precision Inspectors, Testers, and Related Workers:		
Adjusters and calibrators	693	61
Plant and System Operators:		
Water and sewage treatment plant operators	694	62
Power plant operators	695	62
Plant and system operators, stationary engineers	696	62
Other plant and system operators	699	62
OPERATORS, FABRICATORS, AND LABORERS		
Machine Operators, Assemblers, and Inspectors		
Machine Operators and Tenders, Except Precision		
Metal Working and Plastic Working Machine Operators:		
Lathe, milling, and turning machine operatives	703	63
Punching and stamping press operatives	706	63
Rollers, roll hands, and finishers of metal	707	63
Drilling and boring machine operators	708	63
Grinding, abrading, buffing, and polishing workers	709	63
Forge and hammer operators	713	63
Fabricating machine operators, n.e.c.	717	63
Metal and Plastic Processing Machine Operators:		
Molders, and casting machine operators	719	64
Metal platers	723	64
Heat treating equipment operators	724	64
Woodworking Machine Operators:		
Wood lathe, routing, and planing machine operators	726	65
Sawing machine operators and sawyers	727	65
Shaping and joining machine operator (woodworking)	728	65
Nail and tacking machine operators (woodworking)	729	65
Other woodworking machine operators	733	65
Printing Machine Operators:		
Printing machine operators, n.e.c.	734	66
Photoengravers and lithographers	735	66
Typesetters and compositors	736	66
Textile, Apparel, and Furnishings Machine Operators:		

Continued on next page

Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Winding and twisting textile/apparel operatives	738	67
Knitters, loopers, and toppers textile operatives	739	67
Textile cutting machine operators	743	67
Textile sewing machine operators	744	67
Shoemaking machine operators	745	67
Pressing machine operators (clothing)	747	67
Laundry workers	748	67
Misc textile machine operators	749	67
Machine Operators, Assorted Materials:		
Cementing and gluing maching operators	753	68
Packers, fillers, and wrappers	754	68
Extruding and forming machine operators	755	68
Mixing and blending machine operatives	756	68
Separating, filtering, and clarifying machine operators	757	68
Painting machine operators	759	68
Roasting and baking machine operators (food)	763	68
Washing, cleaning, and pickling machine operators	764	68
Paper folding machine operators	765	68
Furnace, kiln, and oven operators, apart from food	766	68
Crushing and grinding machine operators	768	68
Slicing and cutting machine operators	769	68
Motion picture projectionists	773	68
Photographic process workers	774	68
Machine operators, n.e.c.	779	68
Fabricators, Assemblers, and Hand Working Occupations:		
Welders and metal cutters	783	69
Solderers	784	69
Assemblers of electrical equipment	785	69
Hand painting, coating, and decorating occupations	789	69
Production Inspectors, Testers, Samplers, and Weighers:		
Production checkers and inspectors	796	70
Graders and sorters in manufacturing	799	70
Transportation and Material Moving Occupations		
Motor Vehicle Operators:		
Supervisors of motor vehicle transportation	803	71
Truck, delivery, and tractor drivers	804	71
Bus drivers	808	71
Taxi cab drivers and chauffeurs	809	71
Parking lot attendants	813	71
Transport equipment operatives–allocated (1990 internal census)	815	71
Transportation Occupations, Except Motor Vehicles		
Rail Transportation Occupations:		
Railroad conductors and yardmasters	823	72
Locomotive operators (engineers and firemen)	824	72
Railroad brake, coupler, and switch operators	825	72
Water Transportation Occupations:		
Ship crews and marine engineers	829	73
Water transport infrastructure tenders and crossing guards	834	73
Material Moving Equipment Operators:		
Operating engineers of construction equipment	844	74
Crane, derrick, winch, and hoist operators	848	74
Excavating and loading machine operators	853	74
Misc material moving occupations	859	74
Helpers, Construction and Extractive Occupations:		

Continued on next page

Table 1 – *Continued from previous page*

Occupations	**CPS code**	**Aggregation**
Helpers, constructions	865	75
Helpers, surveyors	866	75
Construction laborers	869	75
Production helpers	874	75
Freight, Stock, and Material Handlers:		
Garbage and recyclable material collectors	875	76
Materials movers: stevedores and longshore workers	876	76
Stock handlers	877	76
Machine feeders and offbearers	878	76
Freight, stock, and materials handlers	883	76
Garage and service station related occupations	885	76
Vehicle washers and equipment cleaners	887	76
Packers and packagers by hand	888	76
Laborers outside construction	889	76
Laborers, except farm–allocated (1990 internal census)	890	76
MILITARY OCCUPATIONS		
Military	905	77