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UCI Center for Population, Inequality, and Policy

David Neumark, UC Irvine
Giannina Vaccaro, FORS, LINES

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David Neumark
UCI, NBER, IZA and CESifo

Giannina Vaccaro*
FORS, LINES

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Abstract

Several studies find that there is little sex gap in wages at labor market entry, and that the sex gap in wages emerges (and grows) with time in the labor market. This evidence is consistent with (i) there is little or no sex discrimination in wages at labor market entry, and (ii) the emergence of the sex gap in wages with time in the labor market reflects differences between men and women in human capital investment (and other decisions), with women investing less early in their careers. Indeed, some economists explicitly interpret the evidence this way. We show that this interpretation ignores two fundamental implications of the human capital model, and that differences in investment can complicate the interpretation of both the starting sex gap in wages (or absence of a gap), and the differences in “returns” to experience. We then estimate stylized structural models of human capital investment and wage growth to identify the effects of discrimination and differences in human capital investment, and find evidence more consistent with discrimination reducing women’s wages at labor market entry.

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I. Introduction

Many studies present evidence on how the sex gap in wages evolves from labor market entry and over women's and men's careers. These studies generally find that there is little sex gap in wages at labor market entry, but that the sex gap in wages emerges (and grows) with time in the labor market. This evidence is consistent with (i) there is little or no sex discrimination in wages at labor market entry, and (ii) the emergence of the sex gap in wages with time in the labor market reflects differences between men and women in human capital investment and in other decisions such as hours, career aspirations, etc., with women investing less early in their careers. Indeed, some economists explicitly interpret the evidence this way.

This interpretation, however, may be incorrect, because it ignores two fundamental implications of the human capital model. First, if two otherwise identical workers make different decisions about early human capital investment, the worker who invests more at labor market entry will earn lower wages initially. Thus, among equally productive women and men, if women are investing less early in their careers, then in the absence of wage discrimination their starting wages should be *higher* than men's starting wages, not *equal* to men's starting wages. In this case, evidence of no sex gap in wages at labor market entry could mask a wage penalty for women. Second, early in the career the effect of greater human capital investment – in particular, a slower tapering off of human capital investment – can imply slower, not faster wage growth with experience, because the negative effect of current human capital investment on wages outweighs the effect of past human capital investment on wage growth.[1]

Thus, the evidence in much of the existing literature – no sex wage gap at entry, and lower apparent "returns" to experience for women – could in fact reflect two different

[1] This emphasizes that the coefficient on experience in the human capital earnings function is *not* the return to human capital investment.

phenomena than most interpretations of these findings: first, there could be wage discrimination against women at labor market entry despite no wage gap at entry; and second, women could be investing more in human capital (per unit of labor market experience) early in their careers despite the flatter wage-experience profiles.

To better interpret the evidence on the evolution of wages of women and men, we estimate stylized structural models of human capital investment and wage growth, going back to Mincer (1974).[2] As we show, these structural models are required to obtain an estimate of the wage gap at labor market entry that is not contaminated by different human capital investment decisions of women and men. Conditional on the other controls in the model, viewed as time-invariant productivity shifters, it is more appropriate to interpret *this* estimated wage gap as a measure of "residual" discrimination, based on the "residual wage gap" approach (e.g., Hellerstein and Neumark, 2006; Kunze, 2018).[3] Moreover, these structural models permit us to identify the parameters of human capital investment profiles. Thus, the central value from estimating these structural models is that the estimates permit us to do two things: (i) to separately identify sex discrimination in starting wages and sex differences in initial human capital investment; and (ii) to identify the human capital investment profiles of men and women that underlie the usual coefficients on experience and its square, and hence correctly interpret changes in wages with experience as differences in human capital investment.

II. Prior Studies of the Evolution of the Sex Gap in Wages from Labor Market Entry

Several studies present evidence on how the sex gap in wages evolves from labor market entry, many of which offer interpretations based on discrimination, human capital investment, and other factors. The studies we have identified that estimate both a starting sex

[2] Earlier evidence on structural estimates of these kinds of wage equations, for white men only, was reported in Neumark and Taubman (1995).

[3] These same sources discuss reasons the residual wage gap may not reflect discrimination. With these caveats in mind, in the remainder of this paper, as a short-hand, we refer to this gap as an estimate of discrimination.

wage gap and how this wage gap evolves after labor market entry are summarized in Table 1.

Many of these papers (Polachek, 2008; Manning and Swaffield, 2008; Bertrand et al., 2010; Goldin, 2014; and Stokke, 2016) find that there is little sex gap in wages at labor market entry, but that the sex gap in wages arises (and grows) with time in the labor market.[4] A natural interpretation of this evidence is that there is not sex discrimination in pay at labor market entry, and that the sex gap that arises (and grows) with time in the labor market is likely due to lower human capital investment by women, or other choices they make.[5] Indeed, some of the papers offer this or related explanations, as Table 1 documents.

Polachek (2008) is very clear in arguing that human capital differences and not sex discrimination explain some of the observed patterns of the career evolution of the sex gap in wages. He draws on several different types of evidence: a small or non-existent sex gap in pay for single men and women vs. a larger gap for married men and women; a larger sex gap when children are spaced more years apart; and the relationship between marital and family status and lifetime labor force participation. He also appeals to theoretical arguments that the more intermittent labor force participation of many women will lower their human capital investment, as well as related evidence. Together, he argues that "[c]urrent studies decomposing the gender wage gap grossly underestimate the explanatory power of the human capital model because they fail to account for future expected lifetime labor force participation" (pp. 227-8), and that this can explain most of the sex wage gap, leaving little if any role for wage discrimination. He concludes: "… the human capital investment process, more specifically how gender differences in lifetime work affect human capital acquisition, can explain why there is a gender wage gap…" (p. 230). While Polachek does not explicitly

[4] There are two exceptions in the table. Kunze (2005), using data for West Germany, finds different results, perhaps because of apprenticeship training institutions that generate quite different outcomes. Weinberger and Kuhn (2010) find substantially larger starting wage differences, even in more recent data.

[5] Below, we discuss work by Polachek focusing on human capital decisions made by men and women. There is the possibility, of course, of differences in opportunities for human capital investment offered to men and women by employers. This pertains to the more general issue that controls in wage equations can sometimes themselves reflect discrimination, a question considered by, for example, Gronau (1988).

cite evidence on the absence of a sex gap in wages at labor market entry vs. the emergence of a sex gap after labor market entry, the core of his argument is that post-entry labor market decisions drive the sex gap in wages.[6]

Bertrand et al. (2010) explore differences in the sex gap in earnings in the corporate and financial sectors, considering the possibility of explicit or implicit discrimination. But they find that the earnings gap is non-existent at the outset of careers, and attribute its later emergence in part to career interruptions (as also emphasized by Polachek, 2008). Manning and Swaffield (2008), who report no pay gap at entry but large growth in the sex gap within 10 years after labor market entry, attribute nearly half the gap to human capital – training and the accumulation of experience (and much less to job shopping or other factors).[7]

Goldin has made perhaps the most explicit statement that the absence of a starting sex gap in wages but its emergence over time militates against discrimination being an important determinant of the sex gap in wages, at least in recent data.[8] In interpreting the overall sex gap in earnings, she says: "Does that mean that women are receiving lower pay for equal work? That is possibly the case in certain places, but by and large it's not that, it's something else… it's a pretty small number, this number for wage discrimination once you hold lots of things constant." Instead, she emphasizes that the wage difference emerges over time: "Some of the best studies that we have of the gender pay gap, following individuals longitudinally, show that when they show up right out of college, or out of law school, or after they get their M.B.A. – all the studies that we have indicate that wages are pretty similar then… But further down the pike in their lives, by 10-15 years out, we see very large differences in their pay …

[6] He also cites the possibility that *expected* lower participation by women can lead to less market-oriented schooling, which could generate a wage gap at entry (p. 228) – in which case a starting wage gap might not reflect discrimination. On the other hand, he also notes that what he terms "societal discrimination" may generate some of the sex differences in labor force participation between men and women.

7 The Manning and Swaffield paper helps emphasize the point that the human capital framework is not the sole model that can generate some of the empirical regularities of earnings profiles. For example, interfirm job mobility will typically generate wage growth – and in fact larger wage gains for younger than for older workers, which can generate concavity in the age-earnings profile (Mincer, 1986).

[8] See Dubner (2016).

and a lot of that occurs a year or two after a kid is born, and it occurs for women and not for men. If anything, men tend to work somewhat harder."

Of course, childbearing and greater responsibility for childrearing may figure prominently in the post-entry labor market decisions men and women make, and could also influence pre-entry decisions (such as schooling investments). Looking at data from six countries, Kleven et al. (2019) show that earnings of men and women are similar before parenthood, but diverge sharply after the birth of a first child, with the rapid emergence of a large and persistent penalty for women, while men are unaffected. The evidence across countries varies as to the relative roles of the extensive margin (employment), intensive margin (hours), and wage rate – but in all cases the combined effect of hours and wage effects are substantial. Kleven et al. do not refer specifically to discrimination, but again, the lack of a sex gap in earnings prior to childbirth could be interpreted as indicating little or no role for discrimination. As a result of this work, we pay explicit attention to differences in the evolution of the sex gap in wages for women and men who have children vs. those who remain childless.[9]

III. Interpreting the Evolution of the Sex Gap in Wages in the Context of the Human Capital Model

The previous section notes that empirical regularities regarding the evolution of men's and women's wages often indicate that men and women have very similar starting wages (conditional on covariates), but then men have faster wage growth, and that some interpret this evidence as suggesting that pay discrimination is not an important contributor to the sex gap in wages, and instead indicating that the pay gap emerges over time because of contemporaneous and subsequent decisions women and men make.

[9] Goldin also emphasizes that women value temporal flexibility more, choosing jobs with fewer hours, or the same number of hours but hours that they can choose. And elsewhere, she emphasizes that women and men may choose different occupations because of these factors, leading her to see the path to gender equality as one in which more occupations present career profiles more amenable to women (see Goldin and Katz, 2016).

Regarding starting wages, this line of thinking ignores the potential effect on starting wages of differences in human capital investment. Consider two workers with identical initial productivity, who are paid according to their productivity net of the effects of human capital investment. If one invests more in human capital on the job when beginning to work, their initial wage will be lower. Thus, if wages are determined by productivity as captured in the controls in a wage regression, and by the effects of human capital investment in terms of both foregone current productivity and potentially higher productivity (later), and women invest less in human capital initially, then *in the absence of wage discrimination, women's initial wages should be higher, not equal*. Conversely, in this setting equal starting wages are consistent with wage discrimination against women.

This can be seen formally in the context of Mincer's (1974) model of human capital investment and the returns to experience. Suppose that, as in Mincer's baseline model, human capital investment follows the linearly-declining profile

$$k_t = \max\left\{k_0 - \left(\frac{k_0}{T}\right) \cdot E_t, 0\right\}, \tag{1}$$

where k_t equals the ratio of time spent investing in period t (time for which one is not paid because one is not productive), T is the period over which investments are made, the 0 subscript denotes the initial period, and E_t is experience. (So investment declines linearly in experience, eventually reaching zero.)

In this case, the log wage equation in period t is

$$\ln(w_t) = \omega_0 + rS + \ln\left\{1 - k_0 + \left(\frac{k_0}{T}\right) \cdot E_t\right\} + rk_0 \cdot E_t + \left[-\left(\frac{rk_0}{2T}\right)\right] \cdot E_t^2, \tag{2}$$

where r is the rate of return on post-schooling investments. ω_0 denotes the average individual's (log) productivity "endowment," or productivity absent human capital investment. Equation (2) is the underlying basis of the standard Mincerian log wage equation including linear and quadratic experience terms (although the log term on the right-hand side is omitted, based on a first-order Taylor-series expansion giving an approximately linear function in E).[10]

S is years of schooling. It is written without a t subscript to simplify; S can change in the data as individuals achieve more years of education, but, unlike E, the evolution of S over time is not central to our analysis. Also, note that the rates of return on the two types of human capital are constrained to be the same (r). One can see from equation (2) that, with the Taylor-series expansion of the log term, if the return to on-the-job investment differed from the return to schooling, we would effectively have two moments (coefficients) in three parameters.[11] Moreover, as noted in Neumark and Taubman (1995), the argument that these rates of return are equal can be motivated based on the framework of Willis (1986) and Ben-Porath (1967), where r is the discount rate that individuals apply to both schooling and post-schooling investments in investing up to where marginal returns equal marginal costs.[12]

Turning to the main concern of our paper, the second term in equation (2) – $\ln\left\{1 - k_0 + \left(\frac{k_0}{T}\right) \cdot E_t\right\}$ – reflects the reduction in current wages owing to lower current productivity because of contemporaneous human capital investment. At labor market entry, when $E_t = 0$, wages are reduced in proportion to the fraction of time devoted to human capital investment initially (k_0). Clearly if women invest less (all else the same), so that $k_0^f < k_o^m$ (with superscripts f and m denoting females and males), then $\ln\left(w_0^f\right) > \ln(w_0^m)$ – i.e., in the absence of wage discrimination starting wages should be higher for women.

Consider what this implies for the standard estimation of the "reduced form" log wage

[10] Note that equation (2) is not derived from an explicit optimization problem, but rather from assumptions about how investment affects earnings (decreasing earnings in the current period, and augmenting earnings in future periods by a fixed return), coupled with an assumption about the functional form of the investment profile (in this case, linearly declining). Ben-Porath (1967) shows, in an optimizing framework, that investment declines monotonically over the life cycle, but does not pin down the rate of decline. The linearly-declining profile is the most prevalent assumption used in empirical work, in the sense that it leads to the standard log earnings function with linear and quadratic experience terms.

[11] The same issue arises with the Gompertz specification below, for which the first-order Taylor-series expansion is linear.

[12] In addition, it is difficult to obtain convergence of the nonlinear models (i.e., without doing the Taylor-series expansions) with separate rates of return.

equation (i.e., the standard Mincerian log wage equation), including a dummy for females (F) to test for sex discrimination in pay, and differential growth in wages with experience for men and women (which for simplicity we include only as a linear interaction here, although in the empirical implementation we also do this for the quadratic experience term). This specification is

$$\ln(w_t) = \alpha + \mu S + \beta E_t + \gamma E_t^2 + \delta F + \theta F \cdot E_t.\text{[13]} \qquad (3)$$

Suppose that, corresponding to the evidence described above, we find evidence that $\delta = 0$ and $\theta < 0$ – that is, no initial sex gap in wages, and a smaller experience coefficient for women. Interpreting the evidence that $\delta = 0$ (and the absence of evidence that $\delta < 0$) as implying no wage discrimination against women at labor market entry (i.e., at $t = 0$, when $E_t = 0$) is incorrect, because the sex difference in the intercept reflects the influence of both sex discrimination (δ) and initial human capital investment (k_0). In particular, if $k_0^f < k_o^m$, then the estimate of δ in equation (3) is an upward biased estimate of the sex gap in wages (defined as the wage penalty women face).[14]

To see this more formally, modify equation (2) to include different values of the parameter k_0 for men and women, and expand the equation to include a dummy variable for women that will separately identify wage discrimination. So denoting dummy variables for women and men by F and M, we have

[13] Other controls are added to the specifications we estimate. These are detailed in Section IV when describing the data, as well as in the regression Table 2.

[14] As noted earlier, we realize that whether one can test for and estimate wage discrimination in a standard wage regression is an open question. Here, we simply adopt the validity of this framework, focusing on how to interpret δ when the regression controls adequately control for productivity and other differences aside from those related to differences in human capital investment.

$$\ln(w_t) = \omega_0 + (r_f \cdot F + r_m \cdot M) \cdot S$$

$$+ \ln\left\{1 - \left(k_o^f \cdot F + k_o^m \cdot M\right) + \left(\frac{k_o^f \cdot F + k_o^m \cdot M}{T_f \cdot F + T_m \cdot M}\right) \cdot E_t\right\}$$

$$+ \left(r_f \cdot F + r_m \cdot M\right) \cdot \left(k_o^f \cdot F + k_o^m \cdot M\right) \cdot E_t$$

$$+ \left[-\left(\frac{(r_f \cdot F + r_m \cdot M) \cdot \left(k_o^f \cdot F + k_o^m \cdot M\right)}{2(T_f \cdot F + T_m \cdot M)}\right)\right] \cdot E_t^2 + \delta' F. \tag{4}$$

Regarding the intercept, when $E_t = 0$, this equation reduces to

$$\ln(w_t) = \omega_0 + (r_f \cdot F + r_m \cdot M) \cdot S + \ln\left\{1 - \left(k_o^f \cdot F + k_o^m \cdot M\right)\right\} + \delta' F. \tag{5}$$

Equation (5) makes clear that there can be discrimination against women ($\delta' < 0$) even when δ – the estimated coefficient on the female dummy variable in equation (3) – equals zero, when $k_o^f < k_o^m$.[15] That is, without estimating a structural wage equation, we cannot separately identify the effect of discrimination from a sex difference in initial human capital investment.[16]

The interpretation of lower early wage growth for women than for men as implying less human capital investment by women ignores a second implication of the human capital model. Put simply, the estimated coefficients on experience variables in a log wage equation cannot be interpreted as "returns" to human capital investment. In the human capital investment profile in equation (1), *T* determines how quickly human capital investment tapers

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[15] In this case, the negative $\delta' F$ term and the positive term $\ln\left\{1 - \left(k_o^f \cdot F + k_o^m \cdot M\right)\right\} = \ln\left\{1 - \left[\left(k_o^f - k_o^m\right) \cdot F + k_o^m \cdot (M + F)\right]\right\}$ can offset each other, leading to an estimate of δ in equation (3) that is near zero.

[16] To see this even more clearly, substitute for the log expression in equations (4) and (5) the first-order Taylor series expansion around 1.

$$\ln\left\{1 - \left(k_o^f \cdot F + k_o^m \cdot M\right)\right\} \cong -\left(k_o^f \cdot F + k_o^m \cdot M\right).$$

Then equation (5) becomes

$$\begin{aligned}\ln(w_t) &\cong \omega_0 + \left(r_f \cdot F + r_m \cdot M\right) \cdot S - \left(k_o^f \cdot F + k_o^m \cdot M\right) + \delta' F \\ &= \omega_0 + \left(r_f \cdot F + r_m \cdot M\right) \cdot S - \left(\{k_o^f - k_o^m\} \cdot F + k_o^m\right) + \delta' F,\end{aligned}$$

which makes it clear that we cannot, from equation (3), separately identify discrimination (δ') and the difference in initial investment ($k_o^f - k_o^m$).

off with time in the labor market; when this investment diminishes more slowly (T is large), human capital investment is higher (for the same k_0) in periods before it falls to zero.

However, this slower tapering off of human capital investment generates *slower* wage growth initially, not faster, and hence a *smaller* experience coefficient, because the negative effect of current human capital investment on wages outweighs the effect of past human capital investment on wage growth. This can be seen from equations (1) and (2). If T is higher for women, their investment declines more slowly than that of men's. For lower levels of experience, the higher value of T lowers the return to experience – via the $\ln\left\{1 - k_0 + \left(\frac{k_0}{T}\right) \cdot E_t\right\}$ expression in equation (2) – precisely because the substantial current investment in period t outweighs the wage growth from the prior period to the next from past human capital investment.[17]

We also consider an alternative investment profile proposed by Mincer in which investment declines asymptotically to zero, rather than declining linearly:

$$k_t = k_0 \cdot \exp\left(-\pi E_t\right) . \tag{6}$$

This gives rise to the Gompertz wage function, rather than the quadratic wage function (Mincer, 1974). Without introducing separate parameters by sex (the extension is straightforward), the wage equation becomes

$$\ln(w_t) = \omega_0 + rS + \ln\{1 - k_0 \cdot \exp\left(-\pi E_t\right)\} - \frac{rk_0}{\pi} \cdot \exp(-\pi E_t) . \tag{7}$$

The Gompertz earnings function exhibits strictly monotonically declining investment over the life cycle, as in Ben-Porath (1967). However, it does not generate the declining earnings at high experience that the linearly-declining investment profile does, and which is generally observed in the data (Murphy and Welch, 1990) – although in principle we should only see declines in earnings from depreciation of human capital, which is not incorporated in

[17] This same result can be demonstrated by computing the mixed second partial derivative of log wages with respect to E and T for equation (2). This derivative is negative for small E, implying lower wage growth with experience when investment remains higher (T is large), but becomes positive for larger values of E.

the structural specifications above.[18]

All of the preceding discussion of the implications of the underlying human capital investment profile for identifying and interpreting the starting sex gap in wages and "returns" to experience carry over to this specification. We report estimates based on equation (7) as well to assess the robustness of our conclusions.

Finally, the human capital earnings functions developed by Mincer apply to workers who for the most part work continuously after leaving school. When work (labor force participation) is discontinuous, on-the-job human capital investment is also likely to be discontinuous and not monotonically declining with experience, in which case these specifications of the human capital earnings are less appropriate (see, e.g., Polachek, 1975; Weiss and Gronau, 1981; Mincer and Ofek, 1982). Consequently, we also report estimates for subsamples for which we measure actual labor market experience to be at least 75 percent of potential labor market experience, and for an even more stringent restriction to those who never had children.

IV. Data

We use the 1997 National Longitudinal Survey of Youth (NLSY97). NLSY97 respondents were aged 12 to 16 years as of December 31, 1996. We include 16 waves in the analysis, from 1997 through 2013.[19] The NLSY97 is a nationally representative survey of individuals that tracks labor market and life experiences of men and women born between 1980 and 1984 in the United States. It gathers detailed information on earnings, work experience, schooling, and training – the key variables needed for our analysis – as well as a host of other rich information. For our purposes, the NLSY97 has the advantage of providing a large number of observations for people at the start of their careers, which we need to study

[18] At the same time, it is important to note that we likely need a richer model to better fit earnings profiles, at least based on the evidence in Murphy and Welch (1990) – although their evidence is based on CPS data in which actual experience cannot be directly measured.
[19] Data collection was annual from 1997 through 2011, and interviews since then are biennial.

the evolution of wages from labor market entry, and it is also fairly contemporaneous.

The analysis includes variables related to human capital (education, experience, training, and wages), individual characteristics (sex, race, marital status, children, location of current residence, union status), and industry and occupation of work.

Our dependent variable is *hourly wages*. Salaried people do not usually report hourly wages in surveys. We use the NLSY97 constructed variable *CV_HRLY_PAY.xx*, which constructs the hourly rate of pay, at employee-type jobs, from survey questions on the rate and time unit of pay.[20] We normalize hourly wages to 2010 dollars based on the CPI, and use the natural log of the hourly wage in our regression analysis. Our education variable is the highest grade completed by the respondent as of the survey date.

Work experience is measured using the NLSY97 created variable *CV_HOURS_WK_YR_ET.xx*, which calculates the number of hours worked by the respondent in each calendar year, and it is created for each employee-type job. According to the NLSY97 documentation, this variable is created for each respondent even if the respondent has worked no jobs in a given year, in which case it is set to zero. As emphasized by the technical documentation of the survey, when both "starting hours" and "current hours" are reported, the latter are used. In our study, work experience is based on the cumulative number of hours worked in the main job, expressed in units of years.[21] We convert to a year measure based on an assumed yearly number of hours based on 40 hours per week and 52 weeks per year (2,080 hours per year).

We also present some results for a subsample of those who worked relatively continuously since leaving school. The structural models of the human capital model that we

[20] The employment section of the NLSY97 differentiates between four types of jobs: employee-type jobs, freelance jobs, self-employment, and military service. Employee-type jobs in the NLSY97 are those in which the respondent has an ongoing relationship with a specific employer. The constructed measure excludes overtime and performance-based pay.

[21] Respondents to the NLSY97 report the number of hours worked per week at each job they might have and perform at the same time. However, job 1 records information of the principal or main job or remunerated activity the individual has performed. We use the information reported for job 1 to construct our variables.

estimate are most appropriate to the human capital investment behavior of those who work more or less continuously, because intermittent work or long spells of unemployment can introduce more complicated patterns of human capital depreciation and investment (e.g., Polachek, 1975; Mincer and Ofek, 1982; Blackburn et al., 1993), as well as affecting pre-market human capital investment that could be reflected in a sex gap in earnings at labor market entry that is unrelated to labor market discrimination (Polachek, 2008).

As in Neumark and Taubman (1995), this subsample was restricted based on the ratio of actual to potential experience; we use a minimum percentage of actual relative to potential experience of 75 percent. For computing this percentage, we use actual experience measured as cumulative weeks worked since leaving school (which can be less than the work experience measure described above owing to work while in school), and potential experience is measured as the years of experience one could accumulate from the actual date of departure from school without interruptions.[22] However, we use the same experience regressor as for the full sample.[23]

In addition, we do some analysis for the subsample of women and men who never had children. This variable is constructed by combining information from two raw variables available in the NLSY97: *BIOADOPTCHILD_SEX*, which reports the sex of biological and adopted children; and *CV_TTL_BIO_CHILD_XRND*, which reports the number of biological children.[24]

[22] We also estimated results for subsamples restricted to those with relatively continuous school enrollment. This was defined as having age at departure from school within 2 years of what this age would have been if the individual would had begun grade 1 at age 6, remained continuously enrolled in school, and completed one grade each year. Results for this subsample were not materially different, and hence are not reported in the paper (but are available upon request).

[23] If we used only experience post-schooling as the regressor, for many observations experience was much lower because they are last enrolled in their mid-to-late 20s, or even later. In this case, the estimates of the quadratic specification were not well-behaved, because of the concavity imposed by the corresponding investment profile without any restriction on the wage-experience profile becoming negatively sloped. However, the estimates for the Gompertz specification (which never leads to a negatively-sloped wage-experience profile) were similar to those reported below.

[24] There were 225 individuals with biological children who did not report the gender of the child, so we use the latter variable as well to capture more accurately the presence of biological or adopted children.

We construct a training measure based on the *cumulative number of hours in a training program* per year. We use this training measure for alternative evidence on human capital investment patterns. Training measures in the NLSY97 provide information about formal training received by respondents aged 16 or older, outside of their regular schooling. We use information regarding the start and stop dates and time devoted to the training.[25] From 1997 through 2003, the questions refer to the number of hours per day and the number of days per week spent in a training program. For subsequent years, the questions refer to number of hours per week and number of weeks per year. We recognize, of course, that this variable only picks up one dimension of post-schooling human capital investment, but it is the best available measure of post-schooling training that the dataset provides.

We include other control variables, including a dummy variable for females, urban residence, coverage by a contract negotiated by a union or employee association,[26] and marital status. The marital status categories include never-married, married, separated, divorced, or widowed. We include a simple dummy variable for currently married.

The NLSY97 includes three-digit 2002 Census industrial and occupation classification codes. We considered three classifications of industries and occupations: (a) coarse grouping, (b) the detailed three-digit grouping, and (c) an intermediate grouping. The coarse grouping is based on combining many of the detailed three-digit categories, resulting in 20 industry and 35 occupational dummies.[27] The intermediate grouping of occupations and industry categories was obtained by using a clustering procedure that combines industry and occupations codes with similar estimated coefficients from the OLS regressions using the three-digit codes. (We explain below why we use a restricted set of industry and occupation

[25] The survey also collects information about the kind of training, how the training is paid for, and what type of certificates and skills are acquired.
[26] Workers are only asked this question with respect to jobs that lasted 13 weeks or more. We assume workers with shorter jobs were not covered.
[27] This coarse grouping is based on aggregations of three-digit industries or occupations. See https://www.nlsinfo.org/sites/nlsinfo.org/files/attachments/12124/NLSY97%202002%20Census%20I%20and%20O%20Codes.pdf.

controls.) Specifically, we use k-means clustering based on OLS estimates of the coefficients of the full set of industry and occupation dummy variables from the OLS log wage regression model in column (5) of Table 2, discussed below. We use 50 industry and 100 occupation clusters.[28]

We only include people who are not self-employed, who do not perform military activities, and who have data on the variables described above. We only study post-schooling observations, defined as cumulative hours of work that start counting from the year after having finished school enrollment. We do not require a balanced panel.[29] We end up with a final analysis sample of 81,444 observations on 8,691 individuals. Descriptive statistics for our full sample are reported in Appendix Table A1, and for the subsample with actual experience greater than or equal to 75 percent of potential experience in Appendix Table A2. Appendix Table A3 restricts instead to those who never had children.

V. Testing the Alternative Interpretations of the Evolution of the Sex Gap in Wages

We present three different types of analyses intended to better understand the evolution of the sex gap in wages over women's and men's careers. First, we estimate standard log wage regressions. Replicating other work that provides the motivation for this paper, these estimates show that there is little evidence of a sex gap in starting wages, but that the sex gap widens with the accumulation of experience – evidence that has been interpreted as implying that there is no wage discrimination against women at labor market entry, and that women engage in less human capital investment early in their careers.

Second, we estimate the structural parameters of the wage equation, using equation (4) above as well as the similar equation corresponding to equation (7), with separate

[28] We verify that OLS regression results using a detailed grouping (3-digit) of industry and occupation categories remain very similar regardless of the number of clusters.
[29] We do not address selection into work or into the sample, as we are skeptical of the kinds of identifying assumptions needed to identify these mechanisms. Still, this does imply that our results have to be interpreted as conditional on working, and that selective attrition could potentially influence evidence on the longer-run evolution of wages.

parameters by sex. These estimates separately identify k_o^f and k_o^m – and hence the difference between them – and δ' – which captures wage discrimination. These specifications also provide estimates of the human capital investment profile.

Third, we look directly at measures of training in our data, to see how the accumulation of training differs between men and women. We do this to, in a sense, test whether the interpretation of the data provided by the structural estimation makes sense, by asking whether the results we get for measured training are consistent with the implications of the parameter estimates of the human capital investment profiles for women and men.

OLS Wage Equation Estimates

Table 2 reports standard OLS log wage regression estimates. Corresponding to equation (3), the data for women and men are pooled. There is a dummy variable for women, and interactions of this dummy variable with experience and its square (with the latter divided by 100). The specifications differ in two other ways. First, we alternatively exclude both industry and occupation dummy variables, and then include occupation dummy variables and then both sets. Second, we vary the detail of the industry and occupation controls. In columns (2)-(3) we use fairly aggregated industry and occupation categories (35 for occupation and 20 for industry), and in columns (4)-(5) we use highly-detailed categories (479 for occupation, and 262 for industry). For the OLS estimation, the inclusion of the highly-detailed categories is not problematic. However, it is for the nonlinear estimation of the structural wage equations, so we also use a clustering procedure (explained in the data section) to reduce the number of industry categories to 50 and the number of occupation categories to 100 – as reported in columns (6) and (7). In doing this, we were guided by the need to reduce the number of industry and occupation categories enough to do the nonlinear estimation, but not so much as to substantively change the estimates relative to those using the highly-detailed industry and occupation categories in columns (4)-(5).[30] Finally, columns (8) and (9) report the estimates for the subsample with more continuous work experience and for individuals who never had children, respectively.

Consider first the estimated dummy variable for females. Given that we include interactions with experience (and its square), the coefficient of the female dummy variable measures the sex difference in wages at labor market entry. In column (1), with no industry or occupation controls, the estimated starting wage gap is approximately 8.5 percent lower wages for women. In columns (2)-(3), with fairly aggregated industry and occupation categories, this gap falls by about half, to 4.6-4.8 percent – as in column (1), strongly statistically significant. However, with the highly-detailed occupation controls in column (4), or industry and occupation controls in column (5), the estimated sex gap in pay is essentially zero (0.1-0.2 percent) and statistically insignificant. With the somewhat more-aggregated industry and occupation controls in columns (6)-(7) we obtain a similar result. There is a small and statistically insignificant sex gap in pay with only occupation controls (1.3 percent), but with industry controls as well it falls to zero.

Column (8) repeats the last specification, but using the subsample with relatively continuous experience. Again, the estimated initial wage gap is small and statistically insignificant. Finally, column (9) imposes a more substantial restriction – to those who never had children. The estimated initial wage gap is again small and statistically insignificant.

Consider next the estimated coefficients on experience. In every specification in columns (1)-(8), the linear interaction between experience and the female dummy variable is negative and significant (in column (3), the t-statistic is 1.94), indicating that at lower levels of experience, where most of the data are concentrated (see the descriptive statistics

[30] One cannot avoid the problem of a high number of industry and occupation dummy variables in the nonlinear estimation by first regressing variables on the highly-detailed industry and occupation dummy variables, and then doing the nonlinear estimation with the residualized variables, because the Frisch-Waugh-Lovell theorem does not apply to nonlinear models.

Appendix Tables A1 and A2), the "return" to experience on wages is lower for women than for men. In contrast, in column (9) the interaction is positive but very small and insignificant, indicating no difference in the experience profile between childless men and women.

To help interpret the differences in both the linear and quadratic experience coefficients, below the estimated experience controls we report the partial derivatives implied by the estimates, evaluated at 0, 1, 5, and 10 years of experience. In columns (1)-(8), the overall estimated "return" to experience is lower for women at 0, 1, and 5 years of experience, and in all columns except (1) and (3) the estimated return to experience is also lower at 10 years of experience (which implies that it is also lower at all intermediate years of experience less than 10). However, the estimates for those who never had children differ a bit; the return to experience is higher for women at 0 and 1 year of experience.

The estimates in columns (4)-(8) reflect the key result that motivates this paper. Once we include detailed job controls, there is effectively no sex gap in starting pay, but the sex gap grows over time owing to the lower estimated coefficients on (or "returns to") experience for women.[31] This is depicted in Figure 1, using the estimates from columns (7)-(9) of Table 2. Evidence of this sort provides the basis for past interpretations of the evolution of the sex gap in wages as reflecting (a) no wage discrimination at labor market entry, and (b) an increasing wage gap with time in the labor market, reflecting decisions made by women regarding human capital investment (and other factors not incorporated in the human capital earnings function) that influence wages (Bertrand et al, 2010; Goldin, 2014; Manning and Swaffield, 2008; Polachek, 2008; Stokke, 2016).

Structural Wage Equation Estimates

The key question we ask, though, is whether these are accurate interpretations of the

[31] The research literature on the sex gap in pay considers whether including industry and occupation controls "overcontrols" for variables that themselves reflect discrimination (e.g., Neumark, 1988). However, in our context is it important to compare wages in very similar jobs.

data. As we have shown, if women are investing less at labor market entry, then the estimated coefficient on the female dummy variable in Table 2 is an upward biased estimate of the wage penalty faced by women (i.e., potentially obscuring wage discrimination against women) – or of the difference between men's and women's log wages net of investment costs, which is a more appropriate measure of wage discrimination. To obtain an unbiased estimate when there are differences in human capital investment, we need to turn to structural wage equation estimates.[32] And we need structural estimates of the human capital investment profile – and not just the experience coefficients – to assess differences in human capital accumulation.

Table 3 presents nonlinear least squares estimates for the linearly-declining investment profile that underlies the standard Mincerian log wage equation that is quadratic in experience – equation (4).[33] Columns (1) and (2) report results for the full sample, and columns (3) and (4) for the sample with more continuous post-schooling experience.[34] The top rows report estimates of the structural parameters, with the two columns delineating these by sex (e.g., the estimates of k_o^f and k_o^m from equation (4)). The estimates for this specification imply that $k_o^f > k_o^m$ (although the difference is not statistically significant in this case or the other ones we report); these point estimates are *not* consistent with women investing less initially. Consequently, the estimates of δ' – which, recall, is the unbiased estimate of the starting sex gap in pay – are positive and larger than the sex difference in starting pay from reduced-form wage equation estimates (but not statistically significant); this occurs more for the full-sample estimates, for which the difference between the estimates of

[32] Of course, "unbiased" is defined conditional on the structure being correct, which we do not believe is literally true.

[33] Recall that equation (4) is the version of equation (2) that embeds sex differences in all the parameters. Equation (4) indicates that nonlinear least squares estimation is appropriate, as the dependent variable can be written as a nonlinear function of parameters and variables, and an additive error term. The same is true for the Gompertz model discussed earlier and considered below.

[34] We experimented with varying the starting values for the parameters, and found that we either obtained the identical estimates, or for some cases of starting values very far from those reported in Table 3 obtained different estimates at a local but not global minimum (of the least squares criterion).

k_o^f and k_o^m is larger. That is, since, according to the structural estimates, women are investing more initially, which would imply that the estimate of the sex difference in wages that does not take account of initial investment is downward biased; so even the very small negative estimates of the starting wage penalty for women in columns (4)-(8) of Table 2 overestimate the wage penalty faced by women because of discrimination. (Note that this contrasts with the hypothesis discussed in the Introduction – that women may invest *less* initially, in which case the sex difference in starting wages underestimates wage discrimination against women at labor market entry.)

The estimates of T indicate that $T_f > T_m$, which is consistent with women's investments declining more slowly – i.e., with women starting out with higher investments (coupled the higher estimate of k_o^f than k_o^m), and maintaining them longer. As already pointed out, these estimates are not inconsistent with the lower "return" to experience reported in the nonstructural estimates in Table 2, since higher investment both holds down current wages and increases future wages. To see this more clearly in terms of the structural parameters, the bottom four rows of the table show the implied partial derivatives with respect to experience (based on the estimates of equation (4)). Consistent with the OLS estimates, through 10 years of experience the "effect" of experience is higher for men, even though they are investing less; this happens precisely because their investments decline more quickly (consistent with $T_f > T_m$).

Table 4 reports estimates of the Gompertz specification, based on the alternative investment profile in equation (6). In this case, we get somewhat different estimates. For this specification, the estimates for the full sample indicate that $k_o^f \approx k_o^m$, consistent with nearly equal initial investments, while for the restricted sample the estimate of k_o^f is a little smaller. In both cases, again, men's investments decline more quickly (as the estimate of π is larger for men than for women). The key difference, however, is that now the estimate of δ' is negative, consistent with wage discrimination against women in starting pay; this is true in both cases, and for the continuous experience sample the estimate is larger and significant at the 10-percent level. Thus, the application of this structural model gives a qualitatively different view on the evolution of the sex gap in wages, with the estimates indicating that once we estimate this pay gap net of investment differences, women may be underpaid considerably (by around 7-14 percent) at labor market entry. Again, though, women's human capital investment tapers off more slowly, and the bottom of the table shows that the implied "effect" of experience through 10 years of experience is larger for men than for women, although women are clearly investing more early in their careers in the estimates in columns (1) and (2), and doing so after an initial period for the estimates in columns (3) and (4).

One potential issue is that the structural models used thus far are less likely to apply to women with children, who – because of primary responsibility for child care, including labor market interruptions – may have very different optimal human capital investment profiles that do not follow the contours of the Ben-Porath model (e.g., Weiss and Gronau, 1981). We therefore also estimate our models for subsamples of men and women who never have children, for whom we should be able to better isolate the effects of differential treatment by employers.[35]

The results are reported in Table 5. There are, in our view, three findings of note. First, whichever specification we use, the estimates of the structural investment parameters tend to be more similar for men and women. For example, in columns (1) and (2) of Table 3, the estimate of T was 25.95 for women vs. 8.32 for men; in columns (1) and (2) of Table 5, the corresponding estimates are 6.27 and 9.42. The same is true for the estimates of π for the Gompertz specification, and for k_0 (for the quadratic specification). Still, the evidence indicates that women invest less initially (based on the estimates of k_0). Second, as we would

[35] We estimate these models for the subsample of the full sample that never had children, since the discontinuous experience should be less important for these women and men.

expect if children have a greater effect on human capital investment decisions of women, the estimates for women change a good deal, but the estimates for men do not change much. For example, the estimate of T for women in columns (1) and (2) of Table 3 declines from 25.95 to 6.27, while the estimate for men only changes from 8.32 to 9.42. The same is true for k_0 for the quadratic specification, and for π for the Gompertz specification.

Most importantly, though, the estimates of δ' are now negative and fairly similar for both specifications (−0.15 for the quadratic and −0.10 for the Gompertz specification), although both are estimated imprecisely and are statistically insignificant. Thus, using samples for which the monotonically declining investment profiles are much more likely to be appropriate, we now find consistent evidence (although not statistically strong) indicating fairly substantial wage discrimination against women (a 10-15 percent penalty).[36] The negative estimates of δ' are consistent with the estimates of k_0 indicating that women invest less initially, which we find for both specifications.

Evidence on Training Profiles

The qualitative answer obtained thus far – at least regarding initial investment – depends on the structural model assumed. Of course, as usual, both are based on highly stylized assumptions. Thus, for additional evidence we turn to evidence on training as reported in the NLSY97 data.

To that end, Table 6 reports estimates from a regression that corresponds exactly to the wage equation specifications and samples in columns (7)-(9) of Table 2, but with the dependent variable defined as cumulative (100s of hours of) training.[37] In column (1) of Table 6, the estimates do not provide any indication of lower training by females initially –

[36] Note also that these results suggest the less plausible estimate of T for women, in column (1) of Table 3, arises because the monotonically declining investment profile does not provide a good structural model for women who have children.
[37] We use the same clustering of industry and occupation dummy variables so that we can more reliably compare the estimates of the training specification to the estimates of the structural wage equations.

the point estimate is positive (0.033) but insignificant. The point estimate is consistent with the sign of the initial investment gap for the linearly-declining specification in Table 3, while viewing the estimate as zero, it is consistent with the near-equality of k_o^f and k_o^m for the Gompertz specification. The estimated coefficients of experience – which capture the experience profile of training – indicate that, in the early years, women's cumulative human capital investment grows faster. This result is consistent with the estimates for both specifications – the lower estimates of T for men in Table 3, and the higher estimates of π for men in Table 4.

Looking the subsample with more continuous work experience, column (2) differs, with a negative (but insignificant) point estimate for the initial training difference for women. In terms of the point estimates, this is consistent with the estimates of k_o^f and k_o^m in Table 4, where the estimate of k_o^m is larger, but not with the estimates in Table 3, where the estimate of k_o^m is smaller. Still, though, for the subsample in column (2), women's cumulative human capital investment grows faster in the early years in the labor market.

The profiles for these two specifications are shown in the first two panels of Figure 2. Both panels (more so the top one) show women's human capital investment growing faster in the early years in the labor market.

In the estimates in column (3), for those who never had children, the estimated female intercept is positive, consistent with the smaller estimates of k_o^f than k_o^m for both specifications in Table 5. Moreover, there is no evidence that women's training grows faster in the early years in the labor market; the estimated interaction between female and linear experience is very close to zero, and negative (as indicated in the third panel of Figure 2). This is consistent with the smaller estimate of T and the larger (but similar) estimate of π for women. The greater consistency of the results for training and the structural estimates for the subsample that never had children again suggests that the declining investment profiles on which the two sets of structural estimates are based are more appropriate for this subsample.

Interpretation

What are the implications of our evidence? First, our evidence on the discriminatory sex gap in pay at labor market entry is not statistically strong. However, more of the evidence points to a sizable pay gap for women, and perhaps the cleanest evidence – for women and men who never had children – points this way for both specifications. Second, again for this cleanest evidence, the story underlying the difference between the estimated sex gap in starting wages is consistent. Women invest less initially, which implies that the estimated sex gap in starting wages in the reduced-form wage equation is biased upward (toward zero); put the other way, although the reduced-form estimates indicate no sex gap in starting wages, were women and men doing the same initial human capital investment women's starting wages would be lower. The estimates of the Gompertz specification for the subsample with relatively continuous work supports a similar conclusion. Finally, this same analysis yields little evidence that there are sex differences in human capital investment aside from the lower initial investment of women (the difference that obscures evidence of lower starting pay for women in reduced-form wage regressions).

VI. Conclusions

We explore key empirical regularities regarding the evolution of the sex gap in wages over men's and women's careers: that there is little sex gap in wages at labor market entry, but that much of the sex gap in wages emerges (and grows) with time in the labor market. This evidence can be interpreted – and sometimes is – as indicating that there is little or no sex discrimination in wages at labor market entry, and that the emergence of the sex gap in wages over time in the labor market reflects, at least in part, lower human capital investment by women.

We show that this interpretation is potentially at odds with implications of the human capital model, and that without estimating structural models of wage equations embedding parameters describing human capital investment, we can reach the wrong interpretation of both the starting sex wage gap, and the evolution of the sex gap in wages with time in the labor market. We estimate structural earnings equations using two alternative specifications of the human capital investment profile, which help us identify the discriminatory sex gap in wages when there can be sex differences in initial human capital investment, and which provide estimates of sex differences in human capital investment profiles that one cannot infer from estimated effects of experience (and its square) in standard log wage equations.

Our most interesting finding, in our view, is that the data are more consistent with sex discrimination against women at labor market entry, resulting in lower wages, than is suggested by reduced-form wage equation estimates. The structural models we estimate are most appropriate for women (and men) who work relatively continuously. And for the most restrictive such subsample (women and men who never have children), and for one of two specifications with a somewhat weaker sample restriction to those with relatively continuous work, the evidence points to lower initial human capital investment for women and a larger sex gap in starting wages. The point estimates of the starting wage shortfall for women in these cases are approximately 10-14 percent, although in only one case is the estimate significant (at the 10-percent level).

Our estimates and conclusions are clearly based on stylized models of human capital investment and earnings. More complex models could lead to different conclusions. Indeed, prior work on human capital investment makes clear that discontinuous labor market participation could imply quite different optimal human capital investment profiles (Polachek, 1975; Blackburn et al., 1993).[38] We have addressed this issue in part by looking at

[38] Related to this issue, there are questions about how best to define "time in the labor market" in assessing evidence like that we present. Most prominently, for example, there are open questions about the implications of differences in job tenure for the same level of labor market experience for human capital investment and the structural parameters that could describe its evolution, stemming in part from questions about whether the returns to job tenure are causal and hence likely reflect specific human capital investment (e.g., Altonji and Williams, 2005).

a subsample with relatively continuous labor market experience, but analyses that more directly incorporate investment profiles associated with discontinuous employment could provide additional (and perhaps different) evidence. Nonetheless, even if our models do not accurately capture the underlying human capital investment profiles, our analysis highlights the potential misinterpretation of the sex differences in both the intercepts and the experience coefficients of standard Mincerian wage equations if one ignores the underlying human capital investment decisions.

References

Altonji, Joseph G., and Nicolas Williams. 2005. "Do Wages Rise with Job Seniority? A Reassessment." *Industrial and Labor Relations Review* 58(3): 270-97.

Ben-Porath, Yoram. 1967. "The Production of Human Capital and the Life Cycle of Earnings." *Journal of Political Economy* 75(4, Part 1): 352-65.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2010. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics* 2(3): 228-55.

Blackburn, McKinley, David E. Bloom, and David Neumark. 1993. "Fertility Timing, Wages, and Human Capital." *Journal of Population Economics* 6(1): 1-30.

Dubner, Stephen J. 2016. "The True Story of the Gender Pay Gap." *Freakonomics* 232. http://freakonomics.com/podcast/the-true-story-of-the-gender-pay-gap-a-new-freakonomics-radio-podcast/.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review* 104(4): 1091-229.

Goldin, Claudia, and Lawrence F. Katz. 2016. "A Most Egalitarian Profession: Pharmacy and the Evolution of a Family-Friendly Occupation." *Journal of Labor Economics* 34(3): 705-46.

Gronau, Reuben. 1988. "Sex-Related Wage Differentials and Women's Interrupted Labor Careers—the Chicken or the Egg." *Journal of Labor Economics* 6(11): 277-301.

Hellerstein, Judith, and David Neumark. 2006. "Using Matched Employer-Employee Data to Study Labor Market Discrimination." In Handbook on the Economics of Discrimination, edited by W. Rodgers, 29-60. Great Britain: Edgar Elgar Publishing.

Kleven, Henrik, Camille Landais, Johanna Posch, Andreas Steinhauer, and Josef Zweimueller. 2019. "Child Penalties Across Countries: Evidence and Explanations." *American Economic Review* 109(5): 122-26.

Kunze, Astrid. 2018. "The Gender Wage Gap in Developed Countries." In The Oxford Handbook of Women and the Economy, edited by S.L. Averett, L.M. Argys, and S.D. Hoffman, 345-68. New York: Oxford University Press.

Kunze, Astrid. 2005. "The Evolution of the Gender Wage Gap." *Labour Economics* 12(1): 73-97.

Manning, Alan, and Joanna Swaffield. 2008. "The Gender Gap in Early-Career Wage Growth." *Economic Journal* 118(530): 983-1024.

Mincer, Jacob. 1986. "Wage Changes in Job Changes." *Research in Labor Economics* 8(Part A): 171-97.

Mincer, Jacob. 1974. Schooling, Experience, and Earnings. Cambridge: National Bureau of Economic Research, Inc.

Mincer, Jacob, and Haim Ofek. 1982. "Interrupted Work Careers: Depreciation and Restoration of Human Capital." *Journal of Human Resources* 17(1): 3-24.

Munasinghe, Lalith, Tania Reif, and Alice Henriques. 2008. "Gender Gap in Wage Returns to Job Tenure and Experience." *Labor Economics* 15(6): 1296-316.

Murphy, Kevin M., and Finis Welch. 1990. "Empirical Age-Earnings Profiles." *Journal of Labor Economics* 8(2): 202-29.

Neumark, David. 2018. "Experimental Evidence on Labor Market Discrimination." *Journal of Economic Literature* 56(3): 799-866.

Neumark, David. 1988. "Employers' Discriminatory Behavior and the Estimation of Wage Discrimination." *Journal of Human Resources* 23(3): 279-95.

Neumark, David, and Paul Taubman. 1995. "Why Do Wage Profiles Slope Upward? Tests of the General Human Capital Model." *Journal of Labor Economics* 13(4): 736-61.

Polachek, Solomon W. 2008. "Earnings Over the Life Cycle: The Mincer Earnings Function and Its Applications." *Foundations and Trends in Microeconomics* 4(3): 165-272.

Polachek, Solomon W. 1975. "Differences in Expected Post-School Investment as a Determinant of Market Wage Differentials." *International Economic Review* 16(2): 451-70.

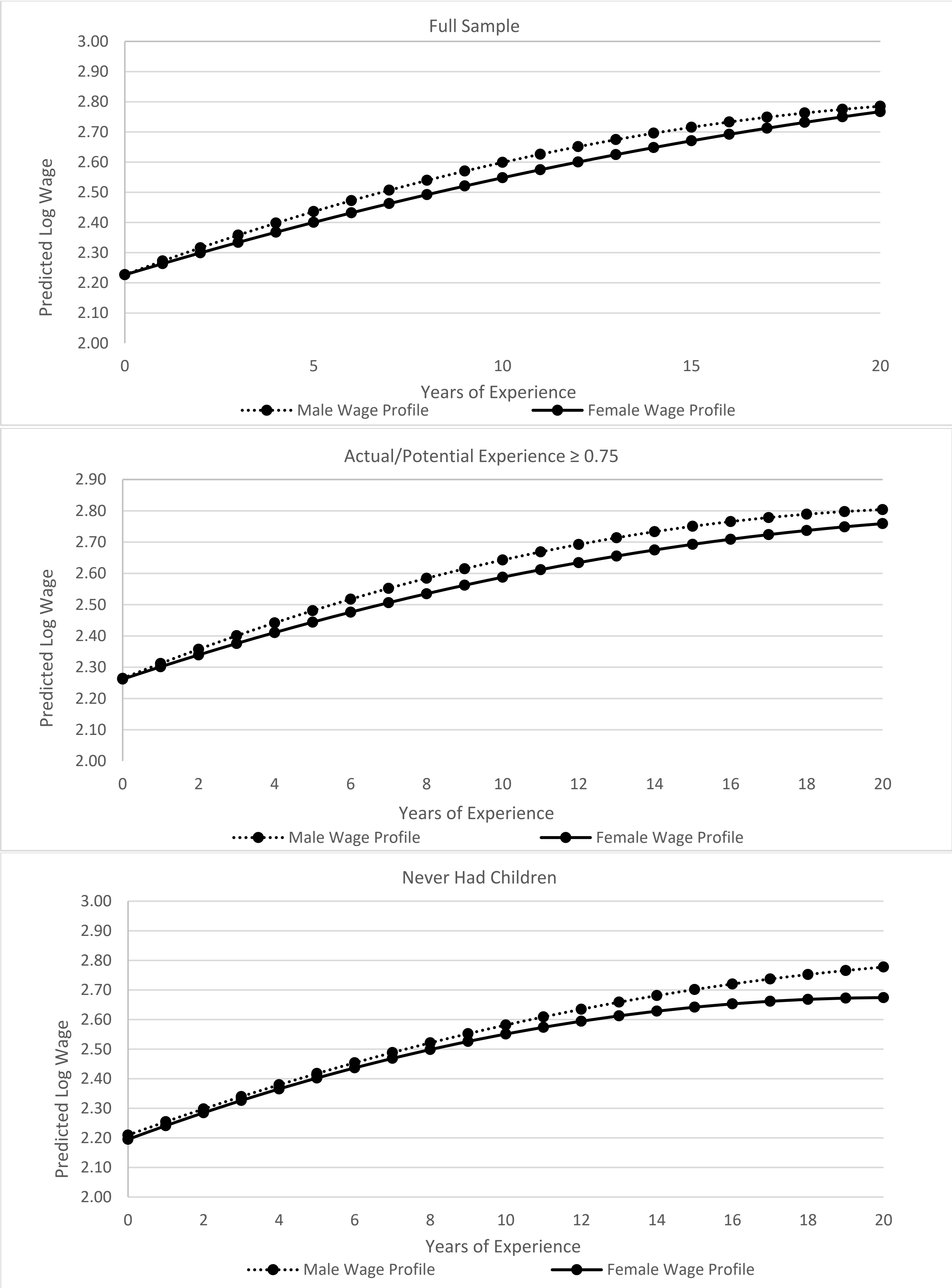
Stokke, Hildegunn E. 2016. "The Gender Wage Gap and the Early-Career Effect." WP No. 2/2016. Norwegian University of Science and Technology.

Weinberger, Catherine, and Peter Kuhn. 2010. "Changing Levels or Changing Slopes? The Narrowing of the Gender Earnings Gap 1959-1999." *Industrial and Labor Relations Review* 63(3): 384-406.

Weiss, Yoram, and Reuben Gronau. 1981. "Expected Interruptions in Labour Force Participation and Sex-Related Differences in Earnings Growth." *Review of Economic Studies* 49(4): 607-19.

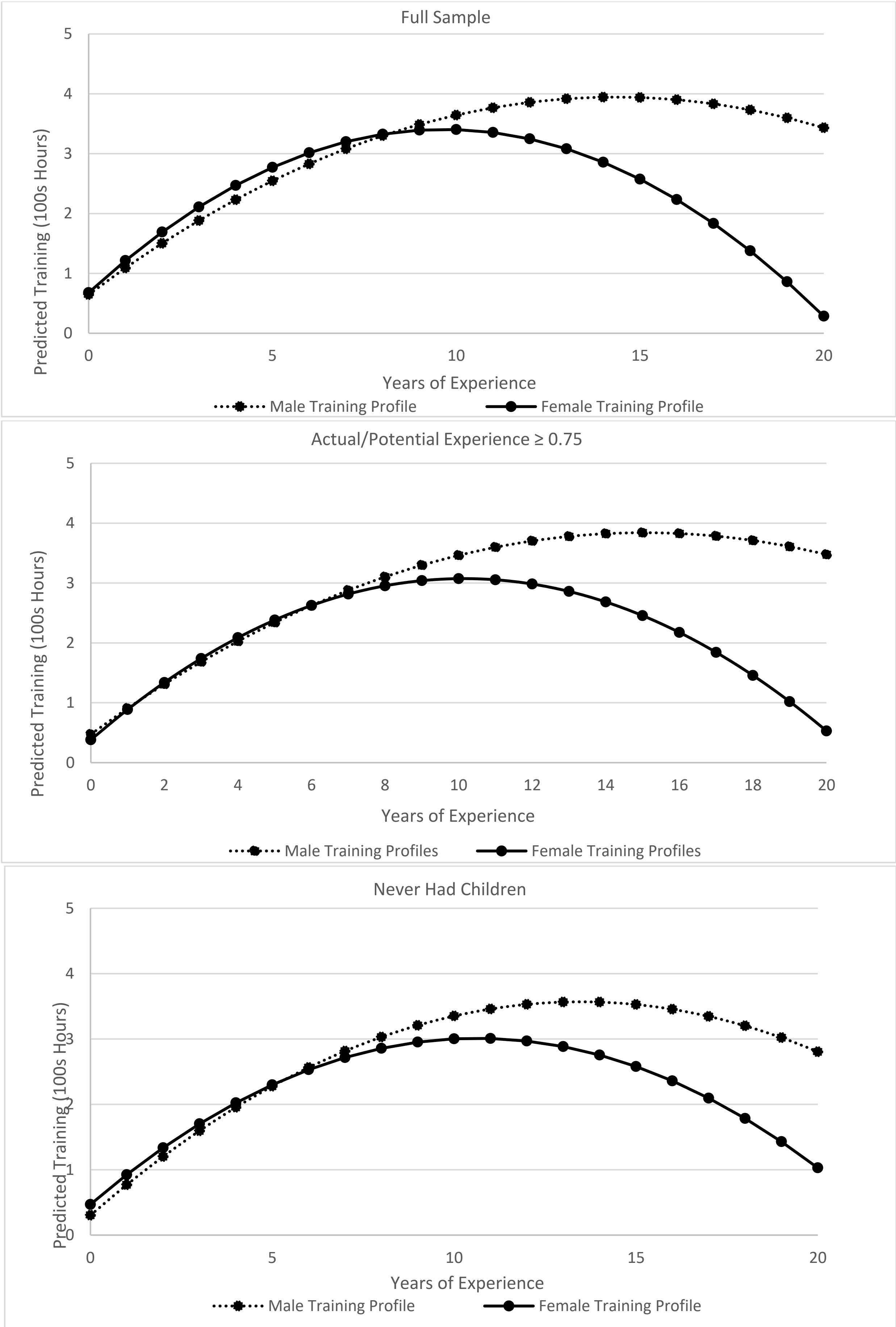
Willis, Robert J. 1986. "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions." In Handbook of Labor Economics, Vol. 2, edited by O.C. Ashenfelter and R. Layard, 525-602. Amsterdam: Elsevier Science Publishers.

Figure 1: Predicted Log Wage Profiles



Notes: The top panel is based on column (7) of Table 2, the middle panel on column (8), and the bottom panel on column (9).

Figure 2: Predicted Training Profiles



Notes: The top panel is based on column (7) of Table 2, the middle panel on column (8), and the bottom panel on column (9).

Table 1: Summary of Studies on Evolution of Sex Gap in Wages/Earnings

	Data	Conclusion	Interpretation/explanation
Polachek (2008)	Luxembourg Income Study (many countries and years)	With female-married interactions included in model, estimated wage gap for (single) women is sometimes very close to zero or even positive (varying from −20% to +4%). Sex wage gap is larger for men and women in families with more years separating younger from older children.	For women, marriage and childbearing are associated with more intermittent labor force participation, which lower human capital investment on the job by making it less valuable (and subject to depreciation).
Munasinghe et al. (2008)	NLSY79 (1979-1994)	Lower effect of experience on wages of women; lower effect of tenure on wages for women.	Driven by higher turnover of women, less training/lower intensity, and lower expectations of working at age 35.
Weinberger and Kuhn (2010)	U.S. Census 1959-2010, CPS 1962-1999	Entry level wage differences vary by cohort (from 19% for young cohorts to 43% for old cohorts). The sex gap does not widen during the earliest years in the career, but it narrows significantly during the life cycle for all cohorts of the U.S. workers. About 32% of decrease in sex wage gap between 1959-1999 is attributed to changes in slopes.	Explanations are mainly focused on explaining wage differences between and across cohorts. Additionally, the decline of discrimination against women is proposed as a complementary explanation for the recent decline in the U.S. sex wage gap. No explanations for the decline of the wage gap throughout the career were provided.
Manning and Swaffield (2008)	British Household Panel Study (BHPS), 1991-2002; Labour Force Survey (LFS) and New Earnings Survey (NES)	No pay gap on entry to the labor market, but a mean unexplained wage gap of about 12.5% after 10 years. Even if women had continuous full-time employment, no children (and none desired), and the same personality as a man, women's wages are 8% lower than men's after 10 years.	Wage differences by sex are mainly due to sex differences in on-the-job training and cumulative experience.
Bertrand et al. (2010)	MBA survey, 1990-2006 graduating classes, matched to university administrative data	Identical incomes at career outset; sex gap in earnings expands, reaching 60 log points 10-16 years after MBA completion.	Modest male advantage in training, and rising returns to training with experience; sex differences in career interruptions associated with large earnings losses; growing differences in weekly hours worked with post-MBA experience.
Goldin (2014)	Multiple datasets: U.S. Census 1970, 1980, 1990, 2000; American Community Survey 2004 to 2006 (for 2005), 2009 to 2011 (for 2010); MBAs from University of Chicago Booth School; University of Michigan Law School Alumni Survey Research Dataset.	Within MBAs from Chicago Booth School, and law graduating students from the University of Michigan Law School, no sex wage differences after graduating were found. This sex wage gap raises to about 55 log points after 15 years. In synthetic cohorts using Census and ACS data, men and women begin with fairly similar earnings, but sex gap grows strongly afterwards.	Heterogeneous (initial and growth) wage gaps across occupations are explained because "hours worked" are valued differently across occupations. No explanation is given for the increase of wage gaps over the lifetime within occupations.
Kunze (2005)	Employment statistics sample, Institute für Arbetitsmarkt und Berufsforschung (IABS), 1975-1990, West-German workers with apprenticeship training	Pronounced gap at entry into first employment, which stays virtually constant through the early career (less than 30 years old). Gender occupational segregation explains 52% of gender wage gap. Males' training programs are longer than females'.	Early wage difference attributed in part to higher quality of training schemes for men and women having higher risk of labor market interruption during the early career.
Stokke (2016)	Norwegian employer-employee register data, as of 2008. Conclusions are drawn after comparing workers in the same firm, with the same occupation, and other individual characteristics.	No sex gap in wages at labor market entry; wage gap increases quickly early in career (7% after 5 years, and 10% after 10 years) and then stabilizes.	None offered.

Table 2: OLS Log Wage Regressions

		Aggregations of 3-digit industries or occupations		**Very detailed industry and occupation**		**Clustered industry and occupation**			
		Full sample		Full sample		Full sample		Actual/potential experience 0.75	Never had children
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	**-0.0854**	**-0.0481**	**-0.0463**	**-0.0024**	**-0.0014**	**-0.0125**	**-0.0000**	**-0.0025**	**-0.0144**
	(0.0085)	**(0.0085)**	**(0.0085)**	**(0.0085)**	**(0.0084)**	**(0.0083)**	**(0.0081)**	**(0.0094)**	**(0.0150)**
Female x Experience	-0.0088	-0.0077	-0.0068	-0.0094	-0.0094	-0.0102	-0.0093	-0.0084	0.0012
	(0.0037)	(0.0035)	(0.0035)	(0.0032)	(0.0032)	(0.0032)	(0.0031)	(0.0035)	(0.0063)
Female x ($Experience^2$/100)	0.0495	0.0349	0.0386	0.0323	0.0431	0.0348	0.0418	0.0312	-0.0283
	(0.0293)	(0.0278)	(0.0276)	(0.0245)	(0.0249)	(0.0248)	(0.0249)	(0.0264)	(0.0526)
$\partial \ln(w)/\partial E$ (Female, E = 0)	**0.0616**	**0.0479**	**0.0440**	**0.0427**	**0.0371**	**0.0437**	**0.0372**	**0.0403**	**0.0472**
$\partial \ln(w)/\partial E$ (Female, E = 1)	**0.0592**	**0.0463**	**0.0428**	**0.0411**	**0.0361**	**0.0420**	**0.0362**	**0.0388**	**0.0449**
$\partial \ln(w)/\partial E$ (Female, E = 5)	**0.0495**	**0.0399**	**0.0380**	**0.0346**	**0.0321**	**0.0350**	**0.0321**	**0.0326**	**0.0356**
$\partial \ln(w)/\partial E$ (Female, E = 10)	**0.0375**	**0.0318**	**0.0320**	**0.0264**	**0.0270**	**0.0263**	**0.0269**	**0.0248**	**0.0239**
Experience	0.0704	0.0556	0.0508	0.0521	0.0465	0.0539	0.0465	0.0487	0.0460
	(0.0024)	(0.0023)	(0.0023)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0024)	(0.0041)
$Experience^2$/100	-0.1702	-0.1154	-0.0984	-0.1137	-0.0934	-0.1218	-0.0931	-0.1086	-0.0880
	(0.0165)	(0.0159)	(0.0158)	(0.0151)	(0.0151)	(0.0149)	(0.0148)	(0.0154)	(0.0298)
$\partial \ln(w)/\partial E$ (Male, E = 0)	**0.0704**	**0.0556**	**0.0508**	**0.0521**	**0.0465**	**0.0539**	**0.0465**	**0.0487**	**0.0460**
$\partial \ln(w)/\partial E$ (Male, E = 1)	**0.0670**	**0.0533**	**0.0488**	**0.0498**	**0.0446**	**0.0515**	**0.0446**	**0.0465**	**0.0442**
$\partial \ln(w)/\partial E$ (Male, E = 5)	**0.0534**	**0.0441**	**0.0410**	**0.0407**	**0.0372**	**0.0417**	**0.0372**	**0.0378**	**0.0372**
$\partial \ln(w)/\partial E$ (Male, E = 10)	**0.0364**	**0.0325**	**0.0311**	**0.0294**	**0.0278**	**0.0295**	**0.0279**	**0.0270**	**0.0284**
Years of schooling	0.0547	0.0368	0.0362	0.0351	0.0352	0.0347	0.0355	0.0358	0.0385
	(0.0016)	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0013)	(0.0016)	(0.0028)
Black	-0.0562	-0.0427	-0.0447	-0.0481	-0.0476	-0.0514	-0.0484	-0.0481	-0.0627
	(0.0073)	(0.0065)	(0.0064)	(0.0061)	(0.0060)	(0.0063)	(0.0060)	(0.0068)	(0.0129)
Married	0.1013	0.0722	0.0675	0.0568	0.0534	0.0582	0.0534	0.0557	0.0563
	(0.0083)	(0.0073)	(0.0072)	(0.0067)	(0.0066)	(0.0067)	(0.0065)	(0.0075)	(0.0181)
Urban	0.0590	0.0584	0.0586	0.0597	0.0571	0.0574	0.0573	0.0545	0.0508
	(0.0069)	(0.0062)	(0.0061)	(0.0058)	(0.0057)	(0.0059)	(0.0056)	(0.0062)	(0.0115)
Union	0.2058	0.1916	0.1860	0.1709	0.1666	0.1644	0.1674	0.1628	0.1793
	(0.0097)	(0.0088)	(0.0089)	(0.0082)	(0.0082)	(0.0084)	(0.0081)	(0.0093)	(0.0167)
Constant	1.4307	1.9037	1.8844	2.3050	2.2119	1.8917	2.1760	2.3113	2.2332
	(0.0193)	(0.0244)	(0.0475)	(0.1136)	(0.1193)	(0.0857)	(0.0837)	(0.0383)	(0.0984)
R^2	0.2547	0.3419	0.3527	0.4082	0.4292	0.3987	0.4279	0.4585	0.3955
N	81,444	81,444	81,444	81,444	81,444	81,444	81,444	59,353	26,279
Industry FE			X		X		X	X	X
Occupation FE		X	X	X	X	X	X	X	X
N industry dummies	0	0	20	0	262	0	50	50	50
N occupational dummies	0	35	35	479	479	100	100	100	100

Notes: Standard errors clustered at the individual level are in parentheses. The dependent variable is log real hourly wages. Years of schooling is based the highest grade completed by the respondent. Experience is an hours-weighted measure, measured in years.

Table 3: NLLS Estimates of Log Wage Equation with Linearly-declining Investment Profile (Quadratic Wage Equation)

	Full sample		Actual/potential experience ≥ 0.75	
	(1)	(2)	(3)	(4)
Model estimates	Women	Men	Women	Men
r	0.0362	0.0320	0.0390	0.0328
	(0.0016)	(0.0020)	(0.0021)	(0.0022)
k_0	0.3748	0.2605	0.2726	0.2141
	(0.1018)	(0.0510)	(0.0743)	(0.0461)
T	25.9502	8.3161	12.7280	5.7140
	(18.2965)	(2.9784)	(7.3350)	(2.0616)
δ'	0.1158		0.0039	
	(0.1777)		(0.1172)	
Constant	2.3844		2.3395	
	(0.0731)		(0.0634)	
R^2	0.4255		0.4723	
N	81,444		59,353	
$\partial \ln(w)/\partial E$	Women	Men	Women	Men
E = 0	0.0367	0.0507	0.0401	0.0547
E = 1	0.0356	0.0480	0.0384	0.0513
E = 5	0.0317	0.0383	0.0321	0.0394
E = 10	0.0271	0.0281	0.0250	0.0270

Notes: Standard errors clustered at the individual level are in parentheses. The dependent variable is log real hourly wages. The model also includes the other controls shown in column (7) of Table 2, entered linearly.

Table 4: NLLS Estimates of Log Wage Equation with Asymptotically Declining Investment Profile (Gompertz Wage Equation)

	Full sample		Actual/potential experience ≥ 0.75	
	(1)	(2)	(3)	(4)
Model estimates	Women	Men	Women	Men
r	0.0355	0.0301	0.0400	0.0343
	(0.0016)	(0.0020)	(0.0021)	(0.0023)
k_0	0.4574	0.4584	0.3894	0.4327
	(0.0538)	(0.0242)	(0.0339)	(0.0206)
π	0.0270	0.0501	0.0426	0.0578
	(0.0115)	(0.0093)	(0.0138)	(0.0101)
δ'	-0.0694		-0.1412	
	(0.1169)		(0.0807)	
Constant	2.7238		2.5782	
	(0.0624)		(0.0589)	
R^2	0.4203		0.4683	
N	81,444		59,353	
$\partial \ln(w)/\partial E$	Women	Men	Women	Men
E = 0	0.0390	0.0562	0.0427	0.0589
E = 1	0.0375	0.0519	0.0403	0.0539
E = 5	0.0322	0.0385	0.0322	0.0388
E = 10	0.0269	0.0276	0.0247	0.0269

Notes: Standard errors clustered at the individual level are in parentheses. The dependent variable is log real hourly wages. The model also includes the other controls shown in Table 2, entered linearly.

Table 5: NLLS Estimates of Log Wage Equation with Alternative Investment Profiles for Subsamples of Childless Men and Women

	Quadratic wage equation		Gompertz wage equation	
	(1)	(2)	(3)	(4)
Model estimates	Women	Men	Women	Men
r	0.0410	0.0379	0.0412	0.0384
	(0.0036)	(0.0038)	(0.0036)	(0.0039)
k_0	0.2055	0.2808	0.3980	0.4332
	(0.1084)	(0.0841	(0.0575)	(0.0391)
T	6.2703	9.4229		
	(5.7201)	(5.7401)		
π			0.0517	0.0504
			(0.0267)	(0.0175)
δ'	-0.1499		-0.1016	
	(0.1781)		(0.1402)	
Constant	2.1729		2.4565	
	(0.1445)		(0.1269)	
R^2	0.3869		0.3835	
N	26,279		26,279	
$\partial \ln(w)/\partial E$	Women	Men	Women	Men
E = 0	0.0497	0.0521	0.0506	0.0552
E = 1	0.0467	0.0493	0.0470	0.0511
E = 5	0.0359	0.0393	0.0356	0.0385
E = 10	0.0242	0.0286	0.0259	0.0279

Notes: Standard errors clustered at the individual level are in parentheses. The dependent variable is log real hourly wages. The model also includes the other controls shown in Table 2, entered linearly. Estimates are reported for the subsample of the full sample (from Tables 3 and 4) that never had children.

Table 6: OLS Regressions for Cumulative Training (100s of Hours)			
	Full sample	Actual/potential experience ≥ 0.75	Never had children
Variables	(1)	(2)	(3)
Female	0.0331	**-0.0915**	0.1656
	(0.1162)	**(0.1050)**	(0.2060)
Female x Experience	0.1045	0.0833	-0.0058
	(0.0535)	(0.0552)	(0.0950)
Female x (Experience^2/100)	-1.3173	-1.1298	-0.4563
	(0.4066)	(0.4181)	(0.7314)
∂Training/∂E (Female, E = 0)	**0.5645**	**0.5308**	**0.4789**
∂Training/∂E (Female, E = 1)	**0.5061**	**0.4785**	**0.4338**
∂Training/∂E (Female, E = 5)	**0.2724**	**0.2691**	**0.2535**
∂Training/∂E (Female, E = 10)	**-0.0197**	**0.0074**	**0.0280**
Experience	0.4600	0.4475	0.4847
	(0.0393)	(0.0446)	(0.0723)
Experience^2/100	-1.6038	-1.4871	-1.7981
	(0.2702)	(0.2921)	(0.5956)
∂Training/∂E (Male, E = 0)	**0.4600**	**0.4475**	**0.4847**
∂Training/∂E (Male, E = 1)	**0.4279**	**0.4178**	**0.4487**
∂Training/∂E (Male, E = 5)	**0.2996**	**0.2988**	**0.3049**
∂Training/∂E (Male, E = 10)	**0.1392**	**0.1501**	**0.1251**
Years of schooling	-0.2330	-0.2122	-0.1961
	(0.0273)	(0.0314)	(0.0392)
Black	0.5688	0.3682	0.4127
	(0.1457)	(0.1665)	(0.2255)
Married	0.4568	0.4717	0.3142
	(0.1510)	(0.1752)	(0.4046)
Urban	0.1495	-0.0364	-0.0666
	(0.1204)	(0.1442)	(0.1876)
Union	0.1654	0.3441	0.1752
	(0.1732)	(0.2092)	(0.2470)
Constant	3.0677	2.1908	3.3929
	(1.0400)	(0.6237)	(1.7438)
R^2	0.0554	59,353	0.0714
N	81,444	0.0586	26,279
Industry FE		X	
Occupation FE		X	
N industry dummies		50	
N occupational dummies		100	

Notes: Standard errors clustered at the individual level are in parentheses. The dependent variable is 100s of cumulative hours of training. The clustering if industry and occupation dummy variables is the same as in Table 2, columns (7)-(9), and the subsequent tables.

Appendix Table A1: Descriptive Statistics, Full Sample				
	Mean	Standard error	25th percentile	75th percentile
Log(wage)	2.3845	0.0021	2.0719	2.6774
Education	12.6076	0.0089	11.0000	14.0000
Experience	4.3362	0.0135	1.1365	6.6688
Experience^2/100	0.3359	0.0018	0.0129	0.4447
Female	0.4994	0.0018	0	1
Black	0.2471	0.0015	0	0
Married	0.1793	0.0013	0	0
Urban	0.7946	0.0014	1	1
Union	0.0860	0.0010	0	0
Note: Descriptive statistics of the NLSY97 analysis sample (N = 81,444).				

Appendix Table A2: Descriptive Statistics, Restricted Sample, Actual/Potential Experience ≥ 0.75				
	Mean	Standard error	25th percentile	75th percentile
Log(wage)	2.4384	0.0024	2.1019	3
Education	13.0885	0.0102	12	15
Experience	4.7961	0.0168	1.297596	7.4558
Experience^2/100	39.6592	0.2392	0.0168	0.5559
Female	0.4943	0.0021	0	1
Black	0.2144	0.0017	0	0
Married	0.1883	0.0016	0	0
Urban	0.7928	0.0017	1	1
Union	0.0922	0.0012	0	0
Note: Descriptive statistics of the NLSY97 analysis sample (N = 64,185).				

Appendix Table A3: Descriptive Statistics, Full Sample of Childless Individuals				
	Mean	Standard error	25th percentile	75th percentile
Log(wage)	2.3790	0.0039	2.0687	2.6792
Education	13.0671	0.0156	11	15
Experience	4.0121	0.0228	0.9615	6.2399
Experience^2/100	0.2971	0.0029	0.0092	0.3894
Female	0.4108	0.0030	0	1
Black	0.1992	0.0025	0	0
Married	0.0605	0.0015	0	0
Urban	0.8134	0.0024	1	1
Union	0.0784	0.0017	0	0
Note: Descriptive statistics of the NLSY97 analysis sample (N = 26,279).				