Human Capital Accumulation, Equilibrium Wage-Setting and the Life-Cycle Gender Pay Gap

Noriko Amano-Patiño* Tatiana Baron† Pengpeng Xiao‡

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Abstract

We study how turnover and human capital dynamics shape the life-cycle gender pay gap when employers are forward-looking and able to set gender-specific wage rates. In our equilibrium wage-posting model with learning-by-doing and fertility events, the life-cycle gap can be attributed to worker productivity, job search, employers' endogenous wage-setting, and job productivity. Estimating the model on NLSY79 data, we find that although the high school and college gaps are driven by different forces, employers' wage-setting accounts for one-third of the gap in both groups. Neglecting interactions between turnover and human capital dynamics biases down the estimated role of turnover substantially.

JEL-codes: J16, J24, J31, J64.
Keywords: Gender wage gap, life-cycle, firm heterogeneity, human capital, job search.

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*University of Cambridge, noriko.amanopatino@econ.cam.ac.uk.
†Ben-Gurion University, tatianb@bgu.ac.il.
‡Duke University, pengpeng.xiao@duke.edu.

1 Introduction

The gender wage gap has been a persistent phenomenon even in the world's most developed economies. Despite the gender convergence in labor force participation, education and occupational composition in the US, women's wages have plateaued at below 80% of men's since the 1990s. Moreover, the gender pay gap widens substantially over the life-cycle (Barth, Kerr, and Olivetti, 2017). An extensive literature emphasizes gender differences in human capital accumulation as an important driver of the life-cycle gap, either due to women's weaker labor force attachment (Mincer and Polachek, 1974; Polachek, 1981; Goldin, 2014; Erosa, Fuster, and Restuccia, 2016; Kleven, Landais, and Søgaard, 2019) or due to limited skill accumulation while employed (Barron, Black, and Loewenstein, 1993; Blundell, Costa-Dias, Goll, and Meghir, 2021). However, even after controlling for observable human capital variables, many studies find that an "unexplained" gap persists (see the review in Blau and Kahn (2017)). In a frictional labor market, part of this "unexplained" gap could be attributed to rational and forward-looking employers discounting wages of high turnover groups as they incorporate search costs and lower expected match output. It is thus important to understand employers' wage-setting decisions while investigating both the cross-sectional and life-cycle gender wage gaps, so that policies can target the gender issue at its sources.

In this paper, we study the role of turnover and human capital dynamics in the gender wage gap both in early career as well as over the life-cycle. We do so in a setting in which firms form expectations regarding career interruption of women (due to regular turnover as well as family responsibilities) and incorporate that information when offering wages. The literature on equilibrium wage-posting à la Burdett and Mortensen (1998) postulates that the weak attachment and short match durations of women can be costly for firms in the presence of search frictions, since meetings between workers and firms are sporadic and it takes time to form a new match. Therefore, profit-maximizing employers might transfer expected costs of future turnover into lower wage offers to women. Several studies use equilibrium search models to link turnover patterns to the gender wage gap in the cross-section (Bowlus, 1997; Bowlus and Grogan, 2009; Bartolucci, 2013; Morchio and Moser, 2020). We complement this literature by noting that the costs of turnover might become especially high when skills accumulate fast in employment., In addition, workers' strategies and their reservation wages are also impacted by their job prospects, which include skill accumulation rate in employment. These endogenous interactions between the demand and supply sides of the market can enhance or counteract the intended impact of policies aimed at reducing gender disparities. To sort through human capital and turnover factors and their interactions in the life-cycle gender wage gap, we develop a structural model of wage dynamics, estimate it on 1979 National Longitudinal Survey of Youth (NLSY79) data, and quantify policy counterfactuals in different human capital environments.

Our model features wage-posting by employers, human capital accumulation by workers through learning by doing, and on-the-job search. Labor markets are segregated by gender and education. Within each gender-education group, workers are heterogeneous in initial human capital, and jobs are heterogeneous in productivity. Each job is a broad occupation within a firm, so job moves both within and across firms are considered career advancement. Upon fertility events, both men and women go into a period of non-employment (parental leave) where there is no job search, no contribution to firm output and no human capital accumulation. To reflect the institutional setting in the US during our data period, parental leave is unpaid and only a fraction of workers can retain their jobs upon having a child. We allow for taste-based discrimination as a residual component.

We make three contributions to the literature. First, we extend the cross-sectional studies of Bowlus (1997) and Bowlus and Grogan (2009) to a life-cycle analysis by including human capital accumulation and firm heterogeneity as in Burdett, Carrillo-Tudela, and Coles (2016). We thus provide a structural counterpart to recent empirical studies of the life-cycle gender-wage gap by Card, Cardoso, and Kline (2016) and (Barth, Kerr, and Olivetti, 2017). Second, we highlight that the role of turnover — and in particular, fertility-related career interruptions, — is inextricable from human capital dynamics in explaining the observed gap. When skills accumulate fast in employment, the high-turnover group (women) fall behind faster in their level of human capital relative to the more stable workers (men). More than that, optimizing employers have an incentive to penalize lower labor market attachment of women more heavily when skills accumulate fast on the job. We illustrate the mechanisms of these interactions and quantify them. Third, we contribute to the vast and still growing literature on the impacts of fertility on the gender wage gap by explicitly modeling fertility-related career interruptions, including the share of workers retaining their previous jobs after having a child, the typical durations of non-participation when previous jobs are retained versus when they are not. This allows us to analyze the various dimensions in which fertility-related interruptions differ by gender, and to identify the margins that contribute most to the gender wage gap.

Using the NLSY79, we first document gender-based labor market differences of high school graduates and college graduates that are central to the analysis. We find a substantial gap expansion over the life-cycle, especially for college graduates: high school and college women earn 15 and 7 log points less than men at the beginning of their careers, but these gaps expand to 28 and 33 log points 15 years after leaving school. Over the same years, we find that college women are much more likely to transition into non-employment than college men (59% more), while their job-finding rates in non-employment and job-to-job transition rates are comparable to men's. For high school graduates however, gender disparities in turnover take different forms. Low-skilled women have a much lower job-finding rate in non-employment than low-skilled men (24% lower), a lower job-to-job transition rate (17% lower) while separation rates are comparable. For both college and high school groups, women spend more time in parental leave than men. However, women in the college group generally go back to work sooner than those in the high school group.

We estimate the model on NLSY79 data using the generalized method of moments. Treating the job as an employer-occupation cell, we are able to recover job productivities from the structure of the model based on the moments describing wage distributions and wage gains upon job transitions at different points of the life-cycle. Based on the model estimates, we conduct counterfactuals to decompose the gender wage gap into four additive channels. First, the *human capital channel* captures the difference in productivity gains during employment through learning by doing. Second, the *search capital channel* captures the fact that women's different turnover patterns make them progress through the offer ladder at a different pace than men. Third, the *equilibrium wage setting channel* measures the difference in the prices offered to men and women in the same job for each unit of human capital. Fourth and last, the *job productivities channel* reflects productivity differences between jobs employing men and those employing women.

Our analysis offers new insights into the structure of the wage gap at different stages of the life-cycle for different education groups. We find that gender differences in job productivities are a very important driver of the gap in high school group, but do not matter much for the gap among college educated workers. At the same time, human capital accumulation differences on-the-job are a major factor generating the life-cycle gap for college graduates especially later in life, while human capital gap plays a minor role for less educated workers. Search capital differences — wage improvements due to on-the-job search, — contribute more to the gender wage gap for college graduates than for high school graduates. Finally, equilibrium endogenous wage-setting considerations of the firms that take into account gender-specific characteristics of workers' behavior is almost equally important in both education groups, accounting for around one-third of the gender wage gap over the life-cycle.

Gender differences in turnover prove to be very important drivers of the life-cycle gap, explaining 56% and 35% of gap in the college and high school groups, respectively. Women's turnover patterns might disadvantage them in several dimensions. Some of turnover parameters induce wage discounts from the firms' side, while others disrupt women's search capital or human capital accumulation. Gender differences in separation rates stand out as most important for the college group, contributing to a wage gap of 8 log points between college men and women. For the high school group, low job arrival rates in both unemployment and employment are important factors. In addition, women in both education groups are likely to spend an extended period in non-employment after having children, and these contribute substantially to the gender gap. Such fertility interruptions not only induce wage discounts from the firms, but also lower human capital accumulation and suppress wage growth. For both college and high school groups, women who return to previous jobs after parental leave are not affected much by fertility interruptions. This is because the duration of parental leave is very short for those who are able to retain their jobs, and thus does not severely impact human capital or employer's wage decisions. These results imply that as far as fertility interruptions are concerned, policies targeting women who have to search for a new job after having a child would be especially beneficial for women.

Finally, we stress that human capital accumulation creates sizable interactions with the rest of the gender differences. In particular, increasing the skills' accumulation rate amplifies the effect of an increase in employment stability. This is because when human capital accumulates faster, any increase in work experience due to more stable employment would lead to a larger increase in the human capital stock. At the same time, firms value match stability more when employees' productivity grows faster, and they respond in favor of a higher distribution[1] of wage rate offers. We find that this latter interaction can have major implications on the role of turnover differences for the wage gap. We show that in a framework where firms do not take dynamic human capital accumulation into account, the contribution of gender differences in turnover to the gap can be strongly underestimated.

1.1 Related Literature

A recent empirical literature on the gender wage gap has focused on quantifying the relative importance of within- and across-firm wage changes using matched employer-employee data. Barth, Kerr, and Olivetti (2017) and Goldin, Kerr, Olivetti, and Barth (2017) find that both channels are important. Card, Cardoso, and Kline (2016) find that in Portugal, both sorting across firms and rent-sharing within a firm contribute to the gender wage gap. Our paper provides a structural counterpart to this recent empirical literature by uncovering the mechanisms behind

[1]Or first order stochastically dominant distribution

the across-job and within-job gaps and evaluating a rich set of counterfactual policy exercises. In particular, we highlight the importance of interactions of across-jobs dynamics (turnover) and within-job dynamics (human capital accumulation).

Our work is also related to the growing literature about the impact of fertility on the gender wage gap. Angelov, Johansson, and Lindahl (2016) and Kleven, Landais, and Søgaard (2019) find sizable "child penalties" in women's income and wage trajectories. Erosa, Fuster, and Restuccia (2016) and Adda, Dustmann, and Stevens (2017) develop dynamic models of human capital accumulation, fertility and labor supply choices of women to estimate the impact of having children on the gender wage gap. These papers focus on the decrease in both women's labor supply and human capital after having children. In contrast, we consider the role of employers in setting wages as they anticipate fertility events. We find that these endogenous firm responses account for the bulk of the fertility-related gender wage gap, especially in early career. Albanesi and Olivetti (2009), Gayle and Golan (2012), and Thomas (2019) formulate models of employer statistical discrimination in a competitive market, where men and women have private information about their costs of working during child-rearing years. We take a different approach regarding statistical discrimination. In our model, heterogeneous firms have monopsony power in a frictional labor market, and set wages based on workers' expected labor force attachment as well as strategies of other firms.

The role of turnover differences across gender in frictional labor markets has been explored from a number of angles. Early literature focused on partial-equilibrium effects of career interruptions (Manning, 2000; Manning and Robinson, 2004; Del Bono and Vuri, 2011). Other researchers argued that frictions and gender differences in mobility patterns lead to varying degrees of monopsony power that each firm has towards male and female workers, lowering women's wages (Barth and Dale-Olsen, 2009). The closest work to ours includes Bowlus (1997), Bowlus and Grogan (2009), Bartolucci (2013) and Morchio and Moser (2020), which use a Burdett-Mortensen-type model to analyze the gender gap in wages that emerge in equilibrium as a result of differences in labor market turnover across genders. These studies focus on the cross-sectional gap, and we complement them by including human capital accumulation over the life-cycle. Our framework contributes to this literature by distinguishing the direct effects of interruptions on the worker side from the equilibrium wage-setting responses on the employer side. We highlight that both these effects of turnover should be evaluated in conjunction with human capital accumulation.

Finally, our work is related to the concurrent structural literature on the gender wage gap that incorporates firm-specific productivity, and estimates it using linked employer-employee data in the context of Brazil (Morchio and Moser, 2020), Denmark (Bagger et al., 2019) and Finland Xiao (2020). We study the US context and depart from this literature by including human capital accumulation in a tractable way and developing a methodology to recover job productivities from wage data and transitions alone.

The remainder of the paper is organized as follows: Section 2 describes the data we use and provides evidence of differential wage growth between men and women. Section 3 describes the model. Section 4 describes the estimation strategy, Section 5 details our counterfactual exercises and results, and Section 6 concludes.

2 Data

Our data comes from NLSY79, an annual longitudinal dataset following the lives of 12,686 respondents who were between the ages of 14 to 22 in 1979. Participants are interviewed once a year and provide retrospective information on their labor market outcomes and fertility events. For each respondent, the data contains weekly employment status, job transitions, occupation and industry, hourly wage, and number of hours worked.

We focus on the period after individuals have completed their education, and follow them for 15 years in the labor market. We exclude individuals who have never worked during the sample period, and we treat the states of unemployment and out-of-the-labor force as the same non-employment state throughout the paper. We focus on two education groups: the group of individuals with maximum 12 to 15 years of schooling are referred to as "high school graduates," and those who have 16 to 20 years of schooling are "college graduates."[2] In order to avoid confounding gender disparity with racial disparity, we restrict our sample to non-minority individuals. We also restrict the sample to respondents who did not have any child while in school. These restrictions leave us a sample of 1,376 men and 1,331 women in the high school group, and 653 men and 681 women in the college group.[3]

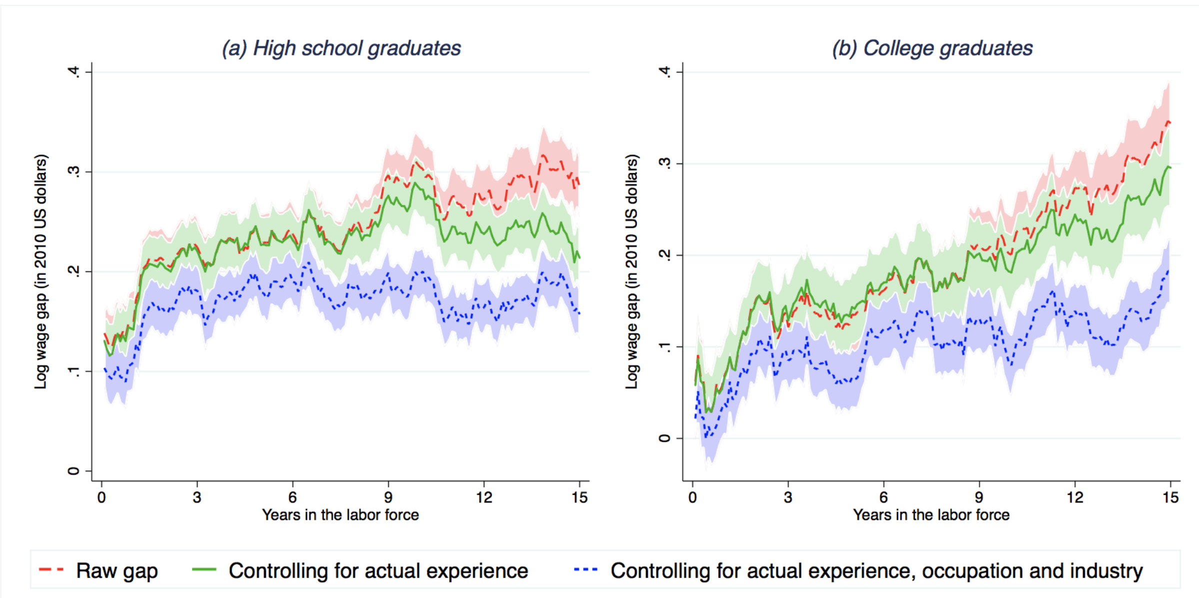
[2]We exclude individuals with more than 20 years of education (Ph.D.s or equivalent) for two reasons. First, because their wage formation and dynamics might be different (Hall and Krueger, 2012) and we have a unified framework for workers across education and gender groups. Second, there are very few individuals in this education group, and most women in this group had children before completing their full time education.

[3]We trim the top and the bottom (which includes many zeros) 3% of the wage distributions, which tend to be thin and cover wide ranges. The reason for this is that the model has a difficult time reconciling these observations that result in sometimes implausible firm productivity values. The choice of a trim level does, of course, have a direct effect on the estimates, but sensitivity analysis done with no trimming and a 3% trim level reveals that the parameters and conclusions of interest are robust.

2.1 Gender wage gaps over the life-cycle

Substantial male and female wage differentials exist even at the beginning of workers' careers. During the first year in the labor market, the initial wage gap is 15 log-points for high school graduates and 7 log points for college graduates. Fifteen years after labor market entry, the gaps increase to 28 and 33 log points for high school and college groups, respectively (see Figure 1).

Figure 1: *Gender wage gap over the life-cycle*



Notes: The lines in the figures above represent the coefficients of the male dummy β_m in each month of potential experience in equation (1): *(i)* raw gap (with only year FEs); *(ii)* adding actual experience controls; and *(iii)* adding occupations and industries controls in addition to actual experience. The shaded areas represent their corresponding 95% confidence intervals.

In order to investigate the factors contributing to the gender wage gap and its expansion over the life-cycle, we first analyze the gap empirically based on the following specification:

$$w_{it} = \beta_0 Male_i + \sum_{m=1}^{180} \Big[\alpha_m \mathbb{1}[M_{it} = m] + \beta_m \left(Male_i \mathbb{1}[M_{it} = m] \right) \Big] + \tau_y + \varepsilon_{it}, \tag{1}$$

where w_{it} denotes the log hourly real wage of individual i in week t, M_{it} denotes the number of months worker i has spent in the labor force (potential experience), and τ_y are calendar year fixed effects. We decompose the gender wage gap by sequentially adding more controls.

Figure 1 shows the log hourly wage gap between men and women by potential experience: *(i)* in the unadjusted specification in equation (1); *(ii)* adding a fourth order polynomial in actual experience to equation (1); and *(iii)* adding occupation and industry fixed effects and their interactions in addition to actual experience.

It is perhaps unsurprising that actual experience explains little of the gap in early years of the career, since experience accumulation has not yet started taking place. Adding occupation and industry fixed effects still leaves a substantial portion of the gap unexplained. The "unexplained" gaps are 17 and 9 log-points on average for high school and college graduates, respectively. This suggests that similarly qualified men and women receive unequal pay for doing similar jobs, potentially due to firms' wage-setting decisions, which we explore further in Section 3.

2.2 Gender differences in turnover

The regressions in Section 2.1 control for a number of observed gender differences: actual experience accumulation, industry and occupational composition. However, there are additional important gender differences in terms of labor market behaviors that might not be reflected in the above observables. In particular, differences in labor market turnover and fertility-related interruptions not only impact workers' actual experiences, but might also impact firms' expectations about workers' future behaviors. Therefore, these differences may impact firms' equilibrium wage-setting and thus account for at least some part of the residual gap in Figure 1. In Section 2.2, we document these gender differences in labor market behaviors in our sample. In Section 3, we lay out our model linking these differences with firms' wage-setting policies in equilibrium.

Table 1 presents several aspects of gender differences related to labor market turnover and fertility interruptions that emerge in the first 15 years of the life-cycle. In these 15 years, high school and college men work 11.7 and 12.8 years, and high school and college women work 10.2 and 11.7 years (i.e., respectively 1.5 and 1.1 years less than their male counterparts). There are also pronounced gender differences in mobility patterns. For the high school group, women's job-finding rate is 24% lower than that of men, and women's job-to-job transition rates are 17% lower than men's. For the college group, the separation rate of women is a striking 59% higher than that of men, potentially driven by family responsibilities. Note that these transition rates are all computed outside of fertility events, which we discuss below.

In order to examine fertility-related career interruptions, we use the information in NLSY79 on the timing of childbirth. Although we do not directly observe parental leave or job protection in the data, we can infer child-related non-employment from the worker's employment history. We assume that a worker is on *parental leave* if she or he is non-employed in any of the first 20 weeks of the child's life. If a worker is not working in the weeks preceding childbirth, these

Table 1: *Summary statistics by gender and education*

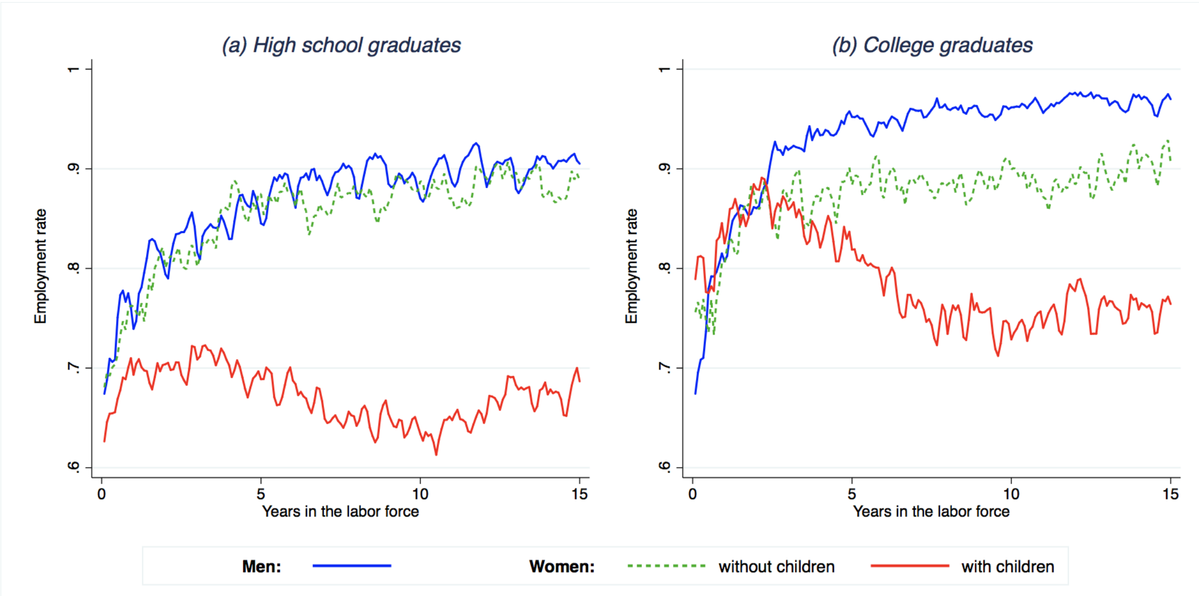
	High school graduates		College graduates	
	Women	*Men*	*Women*	*Men*
Sample size	1331	1376	681	653
Actual experience (years)	10.17	11.69	11.73	12.82
	(0.11)	(0.10)	(0.14)	(0.13)
Number of children	1.49	1.19	1.37	1.28
	(0.03)	(0.03)	(0.05)	(0.05)
Proportion returning to old job after childbirth	69.43%	89.70%	80.58%	95.41%
Duration of non-employment after childbirth...				
if return to old job (months)	1.97	0.32	1.84	0.14
	(0.10)	(0.03)	(0.22)	(0.01)
if start a new job (months)	16.99	4.49	14.81	3.65
	(1.07)	(0.49)	(2.00)	(0.73)
Transition rates outside of childbirth (monthly)				
Job-finding rate	0.168	0.222	0.198	0.220
Separation rate	0.037	0.034	0.025	0.015
Job-to-job transitions	0.038	0.046	0.035	0.036

Notes: This table reports summary statistics over the first 15 years that workers spend in the labor market, in NLSY79.

weeks are counted as parental leave for up to 3 months before the date of birth. Parental leave lasts until the worker is observed working for at least 4 consecutive weeks. We infer that the leave is *job-protected* by the employer if the worker goes back to the same job when parental leave ends.

In our sample, women have slightly higher fertility rates than men. However, women stay in parental leave for each child for a much longer period than men. According to our definitions, women spend about 2 months in job-protected parental leave whereas men spend only a week. Those who do not enjoy job protection spend a much longer time at home with the baby: high school and college women respectively spend 17 and 15 months in parental leave if they do not go back to the same employer, and men in the same situation spend about 4 months. Although most of the childbirths in our sample happened before job protection was mandated by the Family and Medical Leave Act (FMLA) in 1993, it is clear that many firms voluntarily offered job protection to women: 70% of high school women and 81% of college women were able to go back to the same employers after having children. Job protection rates are much higher for men (90% and 95% for high school and college men, respectively), presumably because they go back to work soon after childbirth. These gender differences in job protection and parental leave duration are incorporated into our model.

Figure 2: *Employment rates by motherhood status*

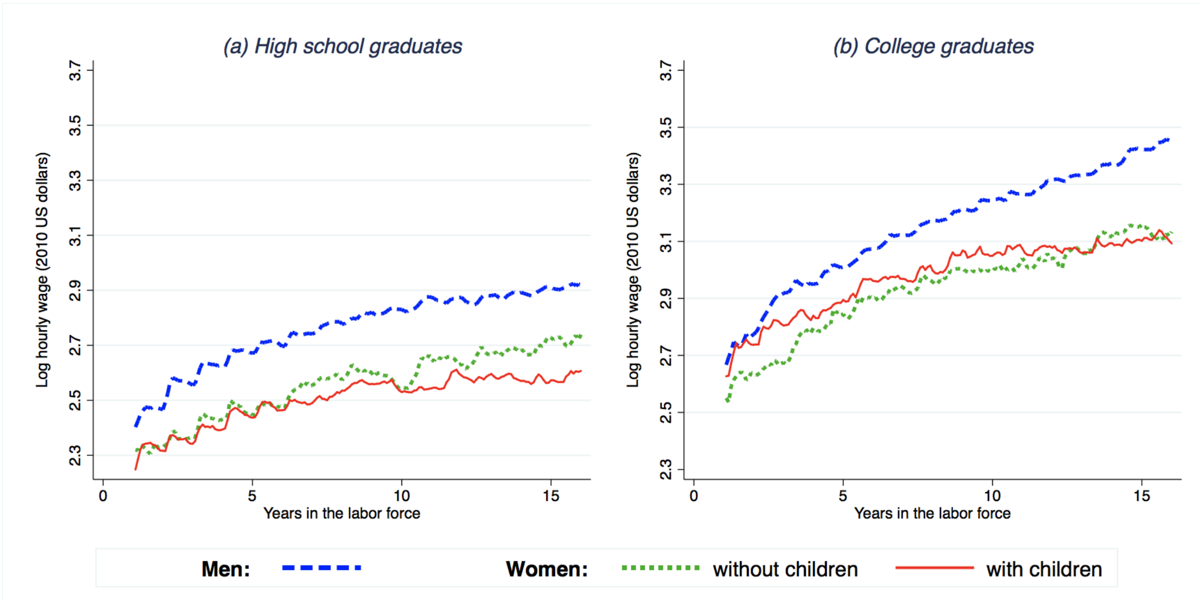


Notes: This figure plots the proportion of workers who are employed during each month after labor market entry. The blue line plots the average monthly employment rate of men, the green dashed line plots that of women who do not have children in our sample period, and the red solid line plots that of women who become mothers at some point during our sample period.

Among the women in our sample, 26% of high school graduates and 34% of college graduates never had any child during the entire sample period, and these women behave more similarly to men in terms of labor force attachment (see Figure 2). If employers could perfectly predict workers' labor market behaviors and fertility patterns, then they would remunerate childless women similarly to men. However, if individual transition rates and fertility interruptions are difficult to foresee, then employers might use gender (and education) to predict the average behavior of the group. That is, if employers anticipate women to be much more affected by childbirth than men, and if these child-related interruptions are costly for firms, then we might expect employers to incorporate some of these costs into wage offers and statistically discriminate against women.

Figure 3 provides suggestive evidence that statistical discrimination might indeed be at play. For the high school group, although childless women have the same employment patterns as men, as noted above, we see that in the first half of the sample period childless women have the same wages as women who eventually do have children, and both earn less than men. Over time, however, the hourly wages of childless women surpass those of women with children,

Figure 3: Wage profiles of women with and without children



Notes: This figure plots the average log wages that workers get each month after labor market entry. The blue dashed-line plots men's average monthly log wages, the green dashed-line plots the average monthly log wages of women who do not have children in our sample period and the red line plots the average monthly log wages of women who become mothers at some point during our sample period.

potentially because the former spend more time working and accumulate more human capital. A similar pattern also emerges for the college group. Childless women who have college degrees also earn lower wages than college men even though their labor market attachment is much closer to men's relative to women with children. Childless women also have lower wages in general than women with children, possibly because of negative selection (Calvo, Lindenlaub, and Reynoso, 2020). Nevertheless, over the course of their careers, childless women accumulate more experience and their wages grow more over time than women with children.

3 Model

Time is continuous and we focus on the steady-state analysis. Men and women separately compose two (exogenously determined) education groups representing high school graduates and college graduates. Each gender-education group is a separate labor market, so that the parameters governing firm productivities, human capital accumulation technology, fertility process, and labor market turnover are all assumed to be gender and education specific. In what follows, we describe workers' and firms' problems in one of the four labor markets. All gender $g \in \{m, f\}$ and skill superscripts $s \in \{\text{Highschool}, \text{College}\}$ are omitted to keep the notation as simple as possible. In this section, we use "she/her/hers" pronouns to refer to a generic worker in the framework. The structure of the model is entirely synonymous for men and women.

There is a continuum of firms and workers. Workers are risk-neutral: they discount the future at rate r and maximize expected discounted lifetime income. They exit the labor market permanently at rate $\phi > 0$, and a new inflow of workers joins the labor market at the same rate.

Each worker enters the market with an initial human capital level, ε, drawn from an exogenous distribution $A(\varepsilon)$ with support $[\underline{\varepsilon}, \overline{\varepsilon}]$. Human capital is general and one-dimensional. While employed, the workers' human capital grows at rate ρ, and we interpret this increase as learning by doing. While unemployed, productivity stagnates. Hence, a type ε worker with actual experience x has productivity $y = \varepsilon e^{\rho x}$.

In the remainder of the paper, we will use the terms *employer* and *job* interchangeably.

Employers are risk neutral and operate according to a constant-returns-to-scale technology. Jobs are occupations within firms and are heterogeneous in productivity, p, drawn from an exogenous distribution $\Gamma(p)$ with support $\left[\underline{p}, \overline{p}\right]$.[4] Every firm posts a wage offer consisting of a single wage rate z to all potential applicants, employed and unemployed. If a worker with productivity y accepts this offer, she matches with the firm and gets paid a wage $w = zy$, reflecting the initial ability of the worker, her actual experience which increases her productivity at rate ρ, and the wage rate z that the firm posts to maximize its steady-state expected profits.[5] The flow productivity of the match (y, p) is yp, so that the firm's flow profit from the match (y, p) is $(p - z)y$. Thus, each firm p chooses an offer z to maximize its aggregated expected steady state profits $\pi(p, z)$ from all the matches that will be formed.[6]

Let $F(z)$ denote the wage offer distribution, the fraction of the firms that offer wage rates no greater than z. This offer distribution is determined in equilibrium through firms' optimal choice of z.[7]

Workers can receive job offers both while unemployed and while employed, according to

[4]The assumption of constant-returns-to-scale means that workers do not compete for the jobs — an employer is ready to hire anyone who finds the offer attractive enough; therefore, we allow for the case when one and the same firm employs both men and women, educated and not, if this firm is in the support of the firms distribution in several submarkets. However, the wage rate is formulated by a firm separately for each submarket.

[5]Since markets are segregated in the model, firms can set gender-specific wages. We could interpret this as firms disclosing the exact wage offer only after observing (or inferring) the candidate employee's gender. Although in practice this type of discriminatory wage is illegal, firms may find ways to circumvent these regulations. In particular, since productivity, y, is unobservable, firms could feasibly claim that women are less productive and offer them lower wage rates.

[6]Informational frictions give monopsony power to firms, which choose to pay less than the marginal productivity. In particular, they pay $w = zy$, where z is a fraction of p — say θ (i.e., $w = \theta py$).

[7]In equilibrium, the distribution F has a bounded support and no mass points. This follows from an analogous argument to the ones given in Burdett and Mortensen (1998).

a Poisson process, and we allow the (exogenously given) arrival rates in each of these states to be different: λ_u while unemployed and λ_e while employed. An employment relationship between a worker and a firm may end for a number of reasons: first, a worker might be poached by another firm offering a higher wage rate z'; second, workers face the risk of separation into non-employment at exogenous rate $\delta > 0$; third, workers are subject to fertility shocks, upon which the worker goes out of the labor force into the parental leave state.

Labor market transitions around fertility events are as follows: a worker can have children in either employment or unemployment at Poisson rate γ_1, upon which the worker leaves the labor force for a period at home with the newborn child. For those who are employed at childbirth, a share η will return to their old jobs — their parental leave period is denoted by *OJ* and ends at rate γ_2. Those who do not return to their old jobs may enjoy a longer time at home — their parental leave is denoted by *NJ* and terminates at a different rate γ_3, upon which they enter a period of unemployment to look for new jobs. Those who are unemployed at childbirth will enter parental leaves of the *NJ* type. We also assume that if the worker has a second child while in *OJ*, she loses the opportunity to return to the old job and goes into the state *NJ*. So at each point in time during the life-cycle, the worker can be employed, unemployed, or out of the labor force in either *OJ* or *NJ* state following childbirth.

The probability that the worker returns to her old job, η, is taken as exogenous in the model. In reality, multiple factors might determine whether a worker retains her job or not, including for example her own willingness and motivation, her relationship with her employer and her employment contract.[8] Unfortunately, our data does not provide any information that helps to distinguish whether the decision of going back to the same job is made by the worker or the employer. Thus, in the model, we assume that a fixed share η of employees retain their jobs after having children, while the share $1-\eta$ return to the labor market as unemployed workers when their parental leave ends.[9]

[8]In the U.S., federally mandated maternity leave was only introduced by the Family and Medical Leave Act (FMLA) in 1993, which provides up to 12 weeks of unpaid, job-protected leave to workers in companies with 50 employees or more. By that time, 80% of our sample had already had their children. Prior to FMLA 1993, parental leave coverage was governed by state laws, collective bargaining agreements and the goodwill of employers.

[9]While treating η as exogenous is a limitation of the model, it also reflects the policy environment of the time — workers might lack information about whether the employer provides job protection, so they assume that they receive job protection with a given probability; employers also do not know how many workers would demand longer periods of PL, and would rather enter unemployment than come back to work.

3.1 Workers' Behavior

In this section, for a given offer distribution F — which will be determined in equilibrium — we characterize optimal workers' behavior.

Consider first an unemployed worker with productivity y, and let $U(y)$ denote the maximum expected lifetime payoff of an unemployed worker with productivity y. Since there is no learning by doing while unemployed (and no depreciation of human capital), we have the following equation describing the value in unemployment $U(y)$:

$$(r+\phi)U(y) = by + \lambda_u \int \max\left\{0, V(y,z') - U(y)\right\} dF(z') + \gamma_1 \left(W^{NJ}(y) - U(y)\right). \tag{2}$$

The flow payoff of the worker is by, which reflects her value of leisure or home production. She gets a job offer (that is, she sees the vacancy posted by a firm which consists of a wage rate offer z') at rate λ_u, and accepts it if the maximum expected lifetime payoff of taking the job is higher than her current value of non-employment $U(y)$. At rate γ_1, the worker has a child, and since she cannot return to a previous job, she enters *NJ*, stops sampling from F, and enjoys $W^{NJ}(y)$, which denotes the value of staying at home with the baby without the possibility to return to her old job.

Now consider a worker with productivity y who is working at a firm paying wage rate z and let $V(y,z)$ denote the maximum expected lifetime payoff she gets. The following equation describes the value function of the worker

$$\begin{aligned}(r+\phi)V(y,z) = zy + \rho y \frac{\partial V(y,z)}{\partial y} + \lambda_e \int \max\left\{0, V(y,z') - V(y,z)\right\} dF(z') \\ + \gamma_1 \left(\eta W^{OJ}(y,z) + (1-\eta) W^{NJ}(y) - V(y,z)\right) + \delta\left(U(y) - V(y,z)\right).\end{aligned} \tag{3}$$

The worker enjoys a flow payoff that is her wage zy. Because of human capital accumulation, the value of employment grows by the amount $\rho y \partial V(y,z)/\partial y$. There is on-the-job search, so the worker receives job offers at rate λ_e and moves to a new firm offering wage rate z' if $V(y,z) < V(y,z')$. Since human capital is both general and transferable across firms, the worker moves to any outside offer z' that is greater than her current wage rate. At rate γ_1 she has a child, and with probability η she enters the old job parental leave state, *OJ*. With the complementary probability, $1-\eta$, she enters *NJ*.

Let us now consider a worker in *OJ* with productivity y who may come back to her previous job paying wage rate z. Her value, $W^{OJ}(y,z)$, is given by

$$(r+\phi)W^{OJ}(y,z) = b^{out}y + \gamma_2\big(V(y,z) - W^{OJ}(y,z)\big) + \gamma_1\big(W^{NJ}(y) - W^{OJ}(y,z)\big). \tag{4}$$

While on leave, the worker gets her flow utility $b^{out}y$, which reflects her value of time with a newborn child. The worker remains "out of the labor force" until the spell at home with the baby ends, at rate γ_2, upon which she will resume her previous job. We interpret γ_2 as related to the average number of months of job protection provided by firms in the labor market. If the worker has another child during the leave period, she loses job protection. Note that the value $W^{OJ}(y,z)$ in the OJ state depends on z, the wage rate offered by the last employer before childbirth.

Finally, let us consider a worker in a parental leave state of NJ type, with value $W^{NJ}(y)$ given by

$$(r+\phi)W^{NJ}(y) = b^{out}y + \gamma_3\left(U(y) - W^{NJ}(y)\right). \tag{5}$$

The worker remains in this NJ state until the alleviation shock, with arrival rate γ_3, allows her to return to the labor force and search for jobs. We interpret γ_3 as the time when family concerns are "alleviated," which could be related to the health of the mother and the baby, the prevalence of daycare, and so on.

As we show in Appendix C.1,[10] the value functions take the following separable form:

$$\begin{aligned} U(y) &= \alpha^U y, \\ V(y,z) &= \alpha^E(z)y, \\ W^{OJ}(y,z) &= \alpha^{OJ}(z)y, \text{ and} \\ W^{NJ}(y) &= \alpha^{NJ}y, \end{aligned}$$

where α^U and α^{NJ} are scalars and $\alpha^E(z)$, $\alpha^{OJ}(z)$ are functions of z. To simplify notation, let us denote the total quit rate by $q(z)$ as follows

$$q(z) = \phi + \delta + \gamma_1 + \lambda_e\overline{F}(z), \tag{6}$$

where $\overline{F}(z)$ denotes the survival function corresponding to $F(z)$.

[10] See equations (15), (16), (17), and (18).

Proposition 1. *For a fixed $F(\cdot)$ with bounded and non-negative support, optimal job search implies that all unemployed workers have the same reservation cutoff z^R, which exists, is unique and is implicitly defined by*

$$\zeta_1\left(z^R-b\right)+\frac{(r+\phi)\zeta_2}{\lambda_u}(b^{out}-b)+\rho\left(b+\frac{\gamma_1}{r+\phi+\gamma_3}b^{out}\right)$$
$$=\left[\zeta_1(\lambda_u-\lambda_e)-\rho\lambda_u+(r+\phi)\zeta_2\right]\int_{z^R}^{\bar{z}}\frac{\overline{F}(z)}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}dz, \qquad (7)$$

where $\zeta_1=r+\phi+\gamma_1-\frac{\gamma_1\gamma_3}{r+\phi+\gamma_3}$ *and* $\zeta_2=\frac{\lambda_u\gamma_1\eta(\gamma_3-\gamma_2)}{(r+\phi+\gamma_3)(r+\phi+\gamma_1+\gamma_2)}$.

Please refer to Appendix C.2 for the proof of Proposition 1.

The Proposition 1 above illustrates one aspect of the equilibrium — the considerations of workers when the distribution of offers $F(z)$ is given. For example, Equation 7 shows that the exogenous separation rate δ, which enters the total separations $q(\cdot)$, brings the reservation rate z^R down. This is because workers value experience and the only way to accumulate it when matches are short-lived is by accepting more offers, which requires lowering the cutoff z^R given the offers distribution $F(z)$. Similarly, workers are ready to forego wages in return for a faster skill accumulation as embodied in ρ. For other parameters it is not possible to verify the sign of their impact on z^R analytically due to the complexity of the expression. In our counterfactual analysis in Section 5, we will provide the intuition for the respective numerical results. Now we turn to the description of the firms' wage-setting problem, which takes z^R as given and develops the complementary building block of our frictional equilibrium.

3.2 Steady-State Flow Conditions

The population of workers in each gender-education group is of measure one and is divided into four subsets: *(i)* the steady-state measure of employed workers, denoted as m_E; *(ii)* that of unemployed workers, m_U; *(iii)* that of workers who are at home with the baby with job protection, m_{OJ}; and *(iv)* that of workers at home with the baby without job protection, m_{NJ}. These steady-state measures have to satisfy the balance-flow conditions detailed in Appendix C.3.

Moreover, the measure of workers below a certain level of human capital x in non-employment, employment, OJ, and NJ states must also remain constant in steady-state equilibrium. Let $N(x)$ and $H(x)$ denote the distributions of accumulated experience among unemployed and employed workers respectively. $N^{OJ}(x)$ and $N^{NJ}(x)$ denote the distributions of experience among workers with and without job protection, respectively. Let $H(x,z)$ denote the joint distribution of experience and wage rates among employed workers, and $H^{OJ}(x,z)$ the joint distribution of workers in parental leave with job protection. Since fertility and job protection are random events, every employed worker has the same probability of having a child and receiving job protection at any point in time, regardless of her wage rate. In other words, $H^{OJ}(x,z) = H(x,z)$.

Characterizations of the measures (m_U, m_E, m_{OJ}, m_{NJ}) as well as the distributions $N(x)$, $N^{NJ}(x)$, and $H(x,z)$ are given in Appendix C.3.

3.3 Firms' Profits

Given the characterization of optimal worker behavior above, we now turn to optimal firm behavior. We provide details and proofs of the contents of this section in Appendix C.4.

We assume that all firms are active and thus they all offer wage rates $z \geq z^R$. A firm with productivity p chooses a wage rate z that maximizes its steady-state expected profit. When a firm with productivity $p \geq \underline{p}$ matches with a worker with human capital y, the flow revenue generated is py and the worker receives a percentage θ of this flow output. In other words, the wage of the worker is $w = \theta py$ and the flow profit of the firm from this match is $(1-\theta)py = y(p-z)$, where $z = \theta p$. Since there is no discounting, the steady-state expected profit for the firm is given by

$$\pi(z,p) = y^{init}(z)\, y^{acc}(z)(p-z),$$

where $\ell(z) = y^{init}(z)\, y^{acc}(z)$ is the total expected human capital available to the firm over the entire expected duration of a match. This expected human capital stock consists of two parts — the first part is the average human capital of new hires that the firm expects to attract, which we denote by $y^{init}(z)$, and the second part is the expected accumulation of human capital as long as the workers stay with the firm, which we denote by $y^{acc}(z)$.

Since the firm can hire from the pool of unemployed workers as well as poach from the pool of employed workers, the expected human capital level of the new hires $y^{init}(z)$ is defined by

$$y^{init}(z) = m_U \lambda_u \int_{\underline{\varepsilon}}^{\overline{\varepsilon}} \varepsilon \int_0^{\infty} e^{\rho x'} dN(x')\, dA(\varepsilon) + m_E \lambda_e \int_{\underline{\varepsilon}}^{\overline{\varepsilon}} \varepsilon \int_{z^R}^{z} \int_0^{\infty} e^{\rho x'} d^2 H(x',z')\, dA(\varepsilon). \qquad (8)$$

Since we do not limit the number of children per worker, the firm must take into account that any worker joining its workforce might have children over the course of her job spell, each time potentially getting an OJ-type parental leave. Since the Poisson process governing fertility is memoryless, regardless of how many children a worker has had in the past, at each point in time, the firm expects the same fertility and the same gains to be collected from the match due to human capital accumulation, $y^{acc}(z)$. We thus define this term recursively as

$$y^{acc}(z) = \int_{\tau=0}^{\infty} \left[q(z)e^{-q(z)\tau} \int_{0}^{\tau} e^{\rho x} dx + \eta \gamma_1 e^{-q(z)\tau} e^{\rho \tau} \int_{\ell=0}^{\infty} \gamma_2 e^{-(\phi+\gamma_1+\gamma_2)\ell} y^{acc}(z) d\ell \right] d\tau. \quad (9)$$

Note that $y^{acc}(z)$ consists of two parts. The first part is the expected accumulation that happens over the duration of the match before any separation takes place — this separation can be due to retirement ϕ, exogenous destruction shocks δ, a transition to a better job $\lambda_e \overline{F}(z)$, or a child shock γ_1 — all elements of $q(z)$ (see equation (6)). The second part of $y^{acc}(z)$ is relevant only in the case where the worker gets an OJ-type parental leave when having a child and she returns to her previous employer after parental leave. The probability that she gets an OJ-type parental leave upon a child shock after a match of length τ is $\eta \gamma_1 e^{-q(z)\tau}$. To ensure that she returns to the previous job, the event of returning to work should occur before retirement or an additional fertility shock — this happens with probability $\gamma_2 e^{-(\phi+\gamma_1+\gamma_2)\ell}$ for any duration of parental leave ℓ.

When the worker returns, the expected events are exactly the same as at the beginning of the match because the Poisson process is memoryless. Thus, the expected accumulated human capital gain will again be $y^{acc}(z)$.

Simplifying equation (9), the firm's problem becomes

$$\max_{z} \quad \frac{(p-z)\widetilde{\varepsilon}}{q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}} \left(m_U \lambda_u \int_0^{\infty} e^{\rho x'} dN(x') + m_E \lambda_e \int_{z^R}^{z} \int_0^{\infty} e^{\rho x'} d^2 H(x',z') \right), \quad (10)$$

where $\widetilde{\varepsilon}$ denotes the expected initial productivity.

We denote the optimal wage rate offer function by $z = \xi(p)$ and show that it is implicitly defined by equation (11) in Proposition 2 below.

Proposition 2. *The optimal policy function, $z = \xi(p)$,*

i) can be expressed as

$$\xi(p) = p - M(\xi(p))^2 \int_{z^R}^{p} \frac{1}{M(\xi(p'))^2} dp', \quad (11)$$

where $M(\xi(p)) = q(\xi(p)) - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \rho$ and

ii) $\xi(p)$ is increasing in p and more productive firms post higher wage offers.

Proposition 2 represents part of the equilibrium that is complementary to Proposition 1. Equation 11? describes firms' wage-setting considerations given the reservation cutoff of the unemployed z^R. For example, given a higher skill accumulation rate ρ and a fixed z^R, employers would be willing to offer higher wage rates at all productivity levels. This is because forces of between-firm competition would make them reward their employees who are now more productive. Similarly, an increase in the exogenous separation rate δ ~~which is part of q~~ would decrease offers, because firms' expected profits from each match would fall, which translates into a discount for the high turnover group. In some cases, like the example of ρ above, firms' and workers' considerations move the offers in opposite directions and it is not possible to determine in advance whichever effect will dominate in equilibrium. We discuss the equilibrium effects numerically in Section 5.

3.4 Definition of Market Equilibrium

The equilibrium is a tuple $\left\{z^R, m_E, m_U, m_{OJ}, m_{NJ}, H(\cdot), N(\cdot), N^{OJ}(\cdot), N^{NJ}(\cdot), H(\cdot,\cdot), H^{OJ}(\cdot,\cdot), F(\cdot), \xi(p)\right\}$ for all $\varepsilon \in [\underline{\varepsilon}, \overline{\varepsilon}]$ and all $p \in \left[\underline{p}, \overline{p}\right]$ such that,

i) $m_E, m_U, m_{OJ}, m_{NJ}, H(\cdot), N(\cdot), N^{OJ}(\cdot), N^{NJ}(\cdot), H(\cdot,\cdot), H^{OJ}(\cdot,\cdot)$ are consistent with steady-state turnover.

ii) Workers' behaviors are optimal and z^R satisfies equation (7).

iii) For any $p \in \left[\underline{p}, \overline{p}\right]$, the firm's optimal offer $z = \xi(p)$ maximizes expected profits and satisfies (11).

Theorem 1 shows that the equilibrium exists and it is unique.

4 Estimation and Results

To bring the model to the data, we derive analytical expressions of key moments in the model by years of actual experience, and match them to their empirical counterparts by GMM. In this section, we outline the parameters of interest and their identification, and summarize the results.

4.1 Model specification and identification

All parameters are specific to the gender and education group. In this section, we continue to suppress the subscripts for simplicity.

We specify a flexible and parsimonious Weibull distribution for both worker and firm heterogeneity. Since NLSY79 provides no data on the firm side (e.g., firm profits or value-added), both worker and firm types are unobserved and we have to make certain assumptions to separately identify the supports of the two distributions. We choose to normalize the minimum worker type $\log(\underline{\varepsilon})$ to zero. For each of the four gender education groups, we specify the workers' initial productivity distribution as $A(\varepsilon) \sim Weibull(\alpha_1, \alpha_2)$ over the support $[1, \infty)$. The productivity distribution of firms employing workers in the gender education group is parametrized as $\Gamma(p) \sim Weibull(\kappa_1, \kappa_2)$ over the support $[\underline{p}, \overline{p}]$.

We consider the reference time period as a month, and fix the following parameters. The retirement rate ϕ is fixed at 0.0033 so that workers have an average of 25 years of prime-age career. Following the literature (Hornstein, Krusell, and Violante, 2011), we assume a monthly discount factor $r = 0.0041$. There are thus fourteen parameters to estimate for each gender and education group — ρ, $\underline{p}$, $\overline{p}$, κ_1, κ_2, α_1, α_2, b, δ, γ_1, γ_2, γ_3, λ_e, and λ_u.

Out of the above fourteen parameters, six have direct data counterparts. We derive closed-form expressions for fertility and turnover moments in the data as functions of the Poisson rates δ, γ_1, γ_2, γ_3, λ_e, and λ_u, independent of the other eight model parameters. The parental leave exit rate in NJ, γ_3, is identified by the difference between regular non-employment duration and a non-employment duration of workers who do not come back to their previous jobs after having a child. Notably, although the job-to-job transition rate of an individual receiving wage rate z is endogenous and depends on both the arrival rate λ_e and the worker's relative position in the offer distribution $F(z)$, the *average* job-to-job transition rate in the economy does not depend on the shape of the endogenous $F(z)$ and is only a function of the Poisson rates in the model. This result follows from the fact that the job-to-job transition rates depend on the *relative rank* of the current wage rate z within the distribution of offers. The details of the analytical derivation are in Appendix D.1.

To estimate the remaining parameters, $\beta = (\rho, \underline{p}, \overline{p}, \kappa_1, \kappa_2, \alpha_1, \alpha_2, b)$, we target the mean, variance, skewness, and kurtosis of log wages evaluated at each year of actual experience, as well as the average wage change during job-to-job transitions. We exploit the tractability of the model and derive all these moments analytically. The details of the analytical solutions are in Appendix D.3.

Given the specification outlined above, all parameters in β are jointly identified by all targeted moments. We provide an intuition for identification in several steps. First, since human capital is general and remains the same when carried over to a new job, the wage change during a job-to-job transition is only related to the changes in human capital prices (the z's) offered in different firms. Therefore, targeting both such wage changes and the overall life-cycle wage growth pins down the human capital accumulation rate ρ which picks up the wage growth remaining after job-to-job transitions. Second, the average wage increase during job-to-job transitions at different points in the life-cycle will inform us about the range and shape of the job ladder $F(z)$. Note that there is a one-to-one relationship between wage offer z and firm productivity p derived from the model that involves transition parameters identified pre-estimation, the human capital parameter ρ identified in the first step above, and income rate in unemployment, b. Another link between b and $\Gamma(p)$ is provided in the third step below.

Third, since wage changes around job-to-job moves are primarily related to the range and the shape of the ladder rather than its location, we augment the identification of the latter by fixing the reservation wage in the model to be equal to the lowest wage observed in the data. Given our normalization of $\underline{\varepsilon}$, the reservation wage rate is a function of ρ (identified in the first step above), b and $\Gamma(p)$ parameters (in particular, it explicitly depends on $\underline{p}$, as shown in the proof of Theorem 1). Therefore, adding this constraint allows us to further distinguish between $\Gamma(p)$ and b. It should be noted that such additional normalizations or restrictions are necessary to distinguish between firm-side and worker-side heterogeneity when using only worker-side data. Recent examples that use similar strategies include Meghir, Narita, and Robin (2015) and Lise, Meghir, and Robin (2016).

The mean log-wage in the first 10 years of actual experience and the average log-wage change upon a job-to-job move in the same years are our two main targets. With 8 parameters of interest for each gender-education cell, the model is already over-identified, but we augment the set of our targets with several higher-order moments over the same years. In particular, any discrepancy in the dispersion and skewness between the data and the model that is not captured by $\Gamma(p)$, b or ρ would inform the distribution of initial productivities $A(\varepsilon)$.

To sum up, our target moments are the first three moments of the log-wage distribution (mean, variance, and skewness) together with the average wage change at job-to-job moves, evaluated at actual experience years from 1 to 10. These add up to 40 moments in total for each gender education group.

Let X be the vector of individual observations in the data, and N denote the number of individuals. Let $f(X,\beta)$ denote the difference between the model-implied target moments and their sample analogues. The GMM estimator of the true $\beta = (\rho, \underline{p}, \overline{p}, \kappa_1, \kappa_2, \alpha_1, \alpha_2, b)$ is then

$$\hat{\beta} = \arg\min_{\beta} \left(\frac{1}{N} \sum_{i=1}^{N} f(X_i, \beta) \right)' W \left(\frac{1}{N} \sum_{i=1}^{N} f(X_i, \beta) \right),$$

where we set the matrix W to be the inverse of the diagonal variance-covariance matrix of the data moments rather than the optimal full variance-covariance matrix because of concerns about bias raised in Altonji and Segal (1996).

4.2 Results and model fit

Table 2 shows the Poisson rates of separation, job-finding and job-to-job transitions, as well as Poisson rates of fertility events. The labor market Poisson rates are in line with the transition probabilities presented in Table 1. Women's separation rates are higher than men's, especially for the college group. Women's offer arrival rates in unemployment are lower than men's, and the difference is more pronounced for the high school group. Men's Poisson exit rates out of parental leave are much higher than women's for both education groups, and men also have a greater probability of going back to the same job after their leave.

Table 2: *Turnover parameters*

		High school graduates			College graduates		
		Women	*Men*	*% difference*	*Women*	*Men*	*% difference*
Separation rate	δ	0.038	0.035	8.0%	0.025	0.016	58.2%
Offer rate in U	λ_u	0.185	0.252	-26.6%	0.222	0.258	-14.1%
Offer rate in E	λ_e	0.092	0.118	-21.9%	0.087	0.087	-0.7%
Fertility rate	γ_1	0.827×10^{-2}	0.663×10^{-2}	24.7%	0.762×10^{-2}	0.709×10^{-2}	7.3%
PL leave exit rate in *OJ*	γ_2	0.496	3.162	-84.3%	0.532	6.892	-92.3%
PL leave exit rate in *NJ*	γ_3	0.022	0.119	-81.8%	0.013	0.305	-95.8%
OJ return rate	η	0.711	0.900	-21.1%	0.822	0.956	-13.9%

Notes: This table reports the values of our calibrated parameters. U = non-employment; E = employment; OJ = parental leave when retaining the old job; NJP = parental leave which ends with a search for a new job. The percentages next to the estimates show the gender differences between the parameters as a percentage of men's.

Table 3 shows the estimates of jointly estimated GMM parameters and their standard errors. All parameters are precisely estimated. We provide the details of the GMM procedure and the computation of standard errors in Section D.2.

The estimates of the human capital accumulation rate show that college men have a much higher ρ than college women, but high school men and women have very similar accumulation rates. The sizable gender gap in ρ for the college group is potentially driven by the nature of the jobs in the high-skill sector, which might entail substantial learning on the job and within-job wage growth. These high-end jobs might disproportionately reward long work hours (as in Goldin (2014)) and provide high returns to job training, and such opportunities for wage growth might be more easily available to men. We interpret the gender difference in ρ to potentially combine various factors (e.g. women might face fewer opportunities for on-the-job training

Table 3: *Jointly estimated parameters*

		High school graduates		College graduates	
		Women	*Men*	*Women*	*Men*
$\boldsymbol{\rho}$		2.614×10^{-3}	2.647×10^{-3}	2.324×10^{-3}	3.196×10^{-3}
		(0.000)	(0.000)	(0.000)	(0.000)
$\boldsymbol{\Gamma}(p)$	$\underline{p}$	6.024	6.704	4.961	6.166
		(0.294)	(0.181)	(0.122)	(0.075)
	$\overline{p}$	20.000	17.927	12.334	14.069
		(0.596)	(1.061)	(0.242)	(0.236)
	κ_1	0.223	0.184	0.956	0.542
		(0.005)	(0.008)	(0.030)	(0.023)
	κ_2	0.240	100.000	17.371	13.729
		(0.012)	(3.684)	(1.479)	(4.203)
$\boldsymbol{A}(\varepsilon)$	α_1	1.314	1.152	1.650	1.399
		(0.036)	(0.027)	(0.067)	(0.034)
	α_2	0.880	0.881	1.340	1.415
		(0.032)	(0.052)	(0.043)	(0.025)
$\boldsymbol{b}$		7.398	9.855	5.888	8.258
		(0.087)	(0.166)	(0.177)	(0.135)

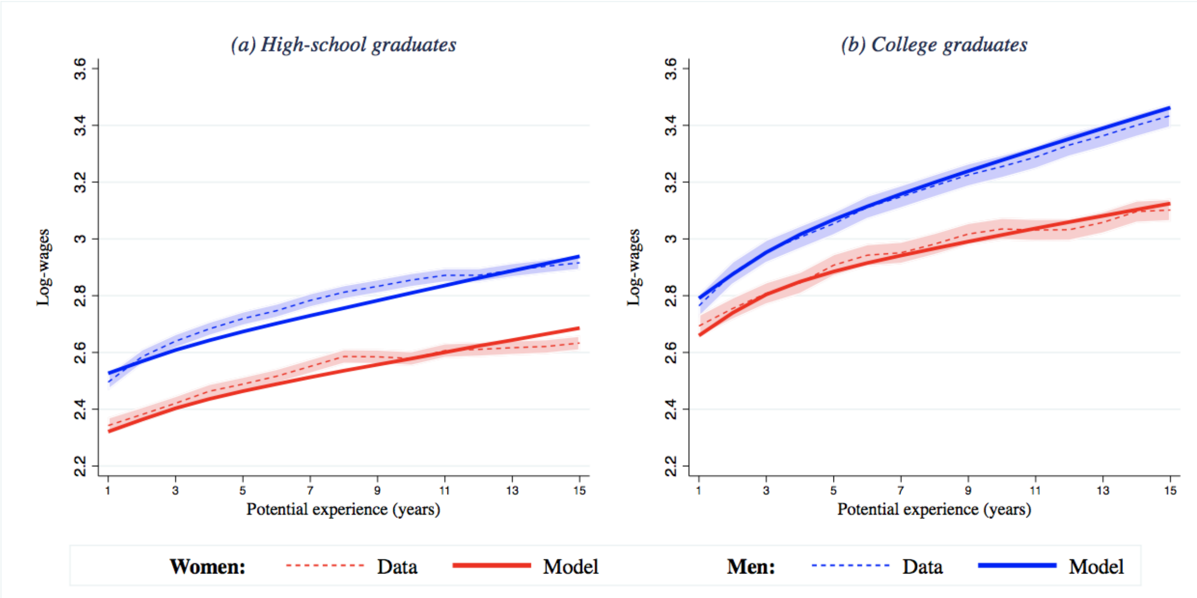
Notes: This table reports the point estimates of the jointly estimated parameters via GMM. The parameters $\underline{p}$, $\overline{p}$, κ_1 and κ_2 govern the firms' productivity distribution, $\Gamma(p)$, and α_1, α_2 determine $A(\varepsilon)$.

than men, women might put more effort into the family than into their careers, and men might have higher wage growth within the firm because they are more likely to bargain for wage raises than women). We remain agnostic about where the ρ difference originates from, but policies that address the above issues might help college women catch up with men in human capital levels.

As would be expected, the support of the firm productivity distribution for men is shifted to the right compared to that for women for both education groups. The shape parameters for workers' initial productivity distributions imply that the mean initial log productivity is almost twice as high in the high-skill market than in the low-skill market. The gender differences within skill groups are moderate — about 4 log points in favor of men in the low-skill group, and about 3 log points in favor of women in the high-skill group. We interpret these gender differences in initial productivities as residual gaps accounted for by a number of factors that we do not model explicitly, such as choice of major and quality of degrees, initial cognitive and non-cognitive skills, and taste-based discrimination (in the labor market or during schooling years).

We show the model fit for all targeted moments in Figure B.1 and Figure B.2. The fit of the two main targets — log-wage profile and log-wage change related to job-to-job transitions, is especially good. Since the model features on-the-job search, it implies that at higher lev-

Figure 4: *Fit of the log-wage profile by years in the labor force*



Notes: The figures show the fit of the model by number of years in the labor market. The solid lines represent the log-wages as predicted by the model, while the dashed lines represent the equivalent data moments.The shaded areas correspond to a point-wise 95% confidence interval.

els of actual experience more and more workers move up the wage offers ladder, compressing conditional wage disparities. In the data, conditional wage differentials increase with actual experience. This could be captured by adding additional productivity shocks to the model. We refrained from doing so for the sake of tractability. Similarly to the data, the model implies that the conditional wage distribution becomes more right-skewed over time, however, it fails to capture the entire degree of the decline in skewness observed in the data. Although we do not target average wages by potential experience, Figure 4 shows that our parameter estimates perform very well in fitting the untargeted moments — log-wage profiles by *potential* experience. Note that these wage profiles combine *(i)* the wage growth by *actual* experience, targeted in the GMM estimation, and *(ii)* the realization of *actual* experience over potential experience, as implied by transition parameters calibrated separately based on turnover data. So Figure 4 shows the fit between model and data for both the jointly estimated parameters and the exogenous transition rates.

5 Counterfactual Analyses

Based on the estimates of the structural parameters, we analyze the drivers of the life-cycle gender wage gap through the lens of the model. The counterfactual exercise in Section 5.1 decomposes the gap into four channels: human capital, search capital, equilibrium wage-setting, and job productivities. Section 5.2 investigates further the mechanisms behind employers' wage-setting channel. Section 5.3 studies the contribution of each parameter to the four channels over the course of the life-cycle. In particular, we offer insights about how human capital dynamics interact with other parameters in both the static wage-setting and over the life-cycle.

5.1 Decomposing the life-cycle gender wage gap

First, we decompose the gender wage gap into four additive parts. Let us denote with $w^g = y^g z^g$ the wages received by workers of gender $g \in \{f, m\}$. We omit the education superscript $s \in$ {High school, College} and the time subscript t in this section to simplify notations, keeping in mind that the decomposition is applicable to any education group at any point of the life-cycle. The expected gender wage gap for a given education group at a given potential experience can be written as

$$\begin{aligned}\overline{gap} &= \overline{\log(w^m)} - \overline{\log(w^f)} \\ &= \underbrace{\overline{\log(y^m)} - \overline{\log(y^f)}}_{\text{gap in HC levels}} + \underbrace{\overline{\log(z^m)} - \overline{\log(z^f)}}_{\text{gap in HC prices}}. \end{aligned} \tag{12}$$

Note that the second term in equation (12), the gender gap in average prices of human capital, can be driven by three factors: first, men and women receive different wage rates on average because they search among different sets of occupations and firms; second, within a given set of firms and occupations, women's mobility to high-premium jobs might be hindered by their weaker labor force attachment; and third, men and women in the same job may be offered different wage rates.

More formally, let $\Omega^g = \{\underline{p}^g, \overline{p}^g, \kappa_1^g, \kappa_2^g\}$ denote the set of parameters governing the productivity distribution of jobs employing workers of gender g, and let $\Theta^g = \{\delta^g, \lambda_e^g, \lambda_u^g, \gamma_1^g, \gamma_2^g, \gamma_3^g, \eta^g, \rho^g, b^g\}$ denote the rest of gender-specific parameters entering the equilibrium wage-setting problem of the firms. Let us also denote with $\Lambda^g = \{\delta^g, \lambda_e^g, \lambda_u^g, \gamma_1^g, \gamma_2^g, \gamma_3^g, \eta^g\}$ the subset of Θ^g containing the parameters that determine the speed with which workers move up the job ladder, including the turnover parameters into and out of employment, and fertility-related interruptions.[11]

Using the above notation, we denote the average counterfactual wage rate at a given point in life by $\overline{\log(z)}\mid_{\Lambda,F(\Omega,\Theta)}$. Note that this average wage rate $\overline{\log(z)}$ is not only conditioned on the endogenous offer distribution $F(\Omega,\Theta)$, but also the speed with which workers climb the job ladder which is governed by Λ. For example, $\overline{\log(z)}\mid_{\Lambda^m,F(\Omega^f,\Theta^m)}$ denotes the counterfactual average wage that men would receive when they face the jobs that employ women (Ω^f), while everything else (Λ^m and Θ^m) remain male parameters. Under this notation, the gender wage gap in equation (12) can be further decomposed as

$$\begin{aligned}\overline{\text{gap}} = & \overbrace{\overline{\log(y^m)} - \overline{\log(y^f)}}^{\textit{Human capital}} + \overbrace{\overline{\log(z)}\mid_{\Lambda^m,F(\Omega^m,\Theta^m)} - \overline{\log(z)}\mid_{\Lambda^m,F(\Omega^m,\Theta^f)}}^{\textit{Equilibrium wage-setting}} \\ & + \underbrace{\overline{\log(z)}\mid_{\Lambda^m,F(\Omega^m,\Theta^f)} - \overline{\log(z)}\mid_{\Lambda^f,F(\Omega^m,\Theta^f)}}_{\textit{Search capital}} + \underbrace{\overline{\log(z)}\mid_{\Lambda^f,F(\Omega^m,\Theta^f)} - \overline{\log(z)}\mid_{\Lambda^f,F(\Omega^f,\Theta^f)}}_{\textit{Job productivities}}.\end{aligned} \tag{13}$$

Equation (13) decomposes the gender wage gap at any given point of the life-cycle into the following four additive channels: *i)* the *human capital channel* captures the difference in wages arising because men tend to accumulate more experience on-the-job than women and also might have a higher productivity growth per unit of experience; *ii)* the *search capital channel* emerges due to the difference between Λ_f and Λ_m, capturing the fact that women's turnover patterns make them progress up the job ladder at a different pace than men; *iii)* the *equilibrium wage-setting channel* reflects the response of the offer distribution $F(\cdot)$ to differences between Θ_f and Θ_m, measuring the difference in the prices per unit of human capital that men and women would be offered in the same job; and *iv)* the *job productivities channel* reflects the difference in mean $log(z)$ arising from the difference between Ω_f and Ω_m, capturing the different productivity levels of the jobs employing men compared to those employing women.[12]

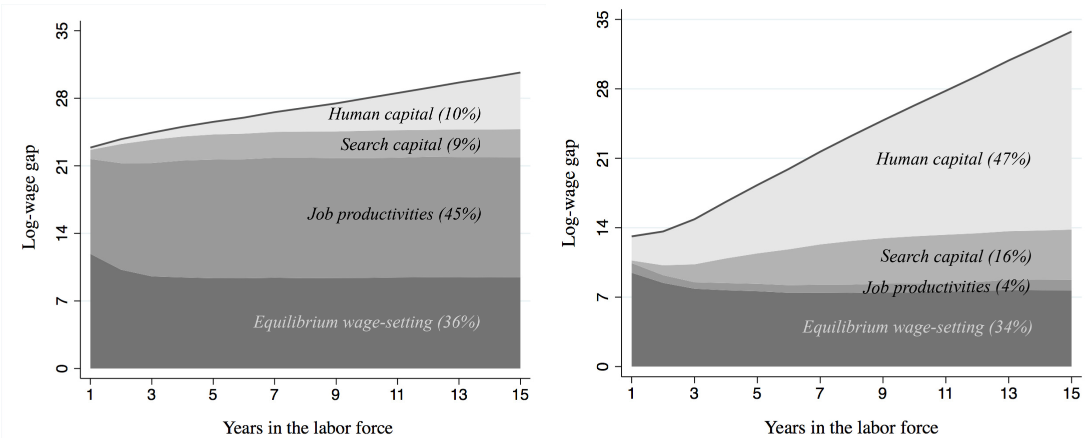
Figure 5 illustrates the relative importance of these four components over the life-cycle. The solid black line represents the total gender wage gap, and the gray areas represent the four additive components outlined in equation (13).

[11] Λ is the set of parameters that affect the search capital channel. Search capital is accumulated to the extent that on-the-job search (governed by λ_e) is uninterrupted. Recall that interruptions can occur either because of childbirth (γ_1) or separation shocks (δ). In case of such an interruption the speed of returning to regain one's search capital depends on the job-finding rate (λ_u) as well as on the parameters governing the return to employment after a fertility event (meaning, η, γ_2, γ_3).

[12] The same decomposition can be done in six different ways depending on the order in which we separate each of the various components. However, we find that quantitatively the resulting decomposition of the gap is stable across all methods.

Figure 5: Decomposition of the gender wage gap over the life-cycle

(a) High school graduates | *(b) College graduates*



Notes: The figure shows the total log-wage gap (black solid line) and its four components (gray areas) as shown in equation (13). In parentheses we show the percentage contribution of each channel averaged over the life-cycle.

In terms of the gender gap *level*,for both education groups, a substantial portion of the total wage gap can be attributed to employers' differential wage-setting towards men and women. On average, this equilibrium wage-setting channel explains around one-third — 36% and 34% of the gender wage gaps for high school and college graduates, respectively. Human capital differences between men and women also contribute to the total wage gap, especially for the college group later in their career. Additionally, men and women search among different sets of jobs, and the size of this job segregation channel is particularly large (45%) for the high school group while for the college group it plays a small role (4%). Finally, men are able to make more job-to-job transitions over the life-cycle, and this search capital difference boosts men's wage rates relative to women by 9% and 16% in the high school and college groups, respectively.[13]

One caveat of our job productivity channel is that it is based on very wide occupation categories in the NLSY97, so it is likely to underestimate the amount of occupational segregation by gender under finer job categories. Although we find that college men and women are almost equally represented in the same (broad) job categories, any promotions within the wide occupation class would not be captured by our job productivity channel. Instead, different rates of advancement within the job category would be attributed to differential returns to human capital in our model. Despite these caveats, our findings are broadly consistent with those in Blau et al. (2013) which show that occupational segregation by gender for the college group was already

[13]The magnitude of the search capital gap in our framework is comparable to the dynamic sorting component found in Card et al. (2016), though they estimate a different model using data from Portugal.

low during the 1970-80s in the US, and it declined much more rapidly than that of less educated workers over the following decades.

In terms of the gender gap *life-cycle expansion*,it is worth noting that the wage gap dynamics over the life-cycle are different between the high school and college groups. While the gender wage gap increases only slightly for high school graduates, the increase is much more pronounced for the college group. For both groups the gap for younger workers is almost entirely driven by two sources — differences in job productivities and equilibrium wage-setting. Since both these sources remain stable over the life-cycle, most of the expansion in the gender wage gap is driven by the human capital and search capital channels , which gain weight in explaining gender wage gap towards later ages, especially for college graduates. The gender gap opening for college graduates is almost entirely driven by the pronounced divergence of human capital paths of men and women. For high-school graduates, one-quarter of the gap expansion is due to differences in search capital between men and women — that is, due to the differences in the speed with which men and women climb the job ladder.[14] We discuss life-cycle dynamics in more detail in Section 5.3.

In Section 5.2 we focus on the *differential wage-setting* portion of the wage gap and explore reasons why firms would offer different wage rates for equally productive men and women. We start with the impacts of individual parameters and then highlight the interactions of turnover parameters and human capital accumulation dynamics for firms' optimal decisions on wage rates offers. While the impact of some (though not all) turnover parameters on the wage offers distribution has been studied in the context of the static gender wage gap (for example, by Bowlus (1997) and Bowlus and Grogan (2009)), their interaction with human capital dynamics and the implications for life-cycle gender wage gap and policy have not yet been explored.

5.2 Steady-state wage-setting by firms

Our model sheds light on the mechanisms behind employers' wage-setting process. Employers choose profit-maximizing wage rates that take into account gender differences in human capital dynamics, labor mobility patterns and fertility-related career interruptions. Thus, the gender gap in offered wage rates is a measure of the differential treatment towards otherwise comparable men and women. Understanding employers' wage-setting rules is crucial for policy-making, because policies aimed at helping workers would be misguided were they to neglect the equilibrium responses of firms.

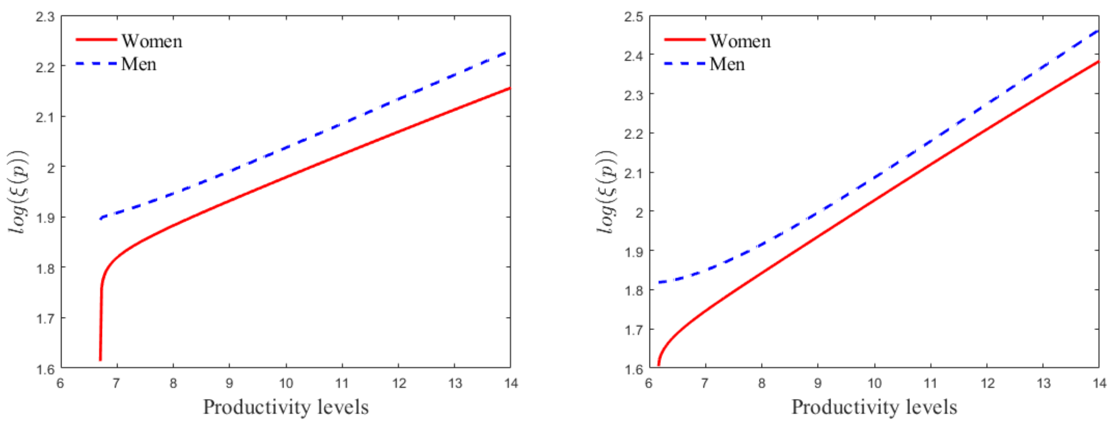
[14] Barth et al. (2017) find that differential progression within-establishment is the major driver of the gender gap expansion for college-educated workers, whereas it matters less for the gap expansion in the high-school group.

In each labor sub-market, a job of a given productivity p offers a profit-maximizing wage rate z according to the policy function given in equation (11) in Section 3.

Figure 6 shows the equilibrium wage rates that would be offered to men and women at each job productivity level, for the high school and college groups respectively. We obtain counterfactual female wage rates in male jobs by computing the equilibrium wage function (see equation (11)) using estimates for men's job productivities and women's human capital, transition rates, and fertility parameters.

Figure 6: *Wage-setting policies by firm productivity*

(a) *High school graduates* ***(b)*** *College graduates*



Notes: The blue dashed lines show the equilibrium wage rates offered to men as implied by the parameter estimates. The red solid lines show the counterfactual wage rates offered to women in the same jobs.

On average, women would get wage offers that are 13 and 10 log points lower than men in the high school and college groups, respectively. There is also considerable variation in the size of these gender gaps across the job productivity distribution. In both groups, the wage discounts towards women are much more pronounced in low-productivity jobs than in high-productivity jobs — the gap is 28 log points in the bottom firms compared with 10 log points in top firms for high-school graduates. For the college group, the differences between offers in low- and high-productivity firms are somewhat milder — 21 and 8 log points, respectively. These marked differences in the wage offers at the low-end do not, however, translate into the differences in average wage rates of the same magnitude, because those unlucky workers who sample wage offers from the very low end of the distribution are able to quickly improve their position through on-the-job search.

In Table 4, we illustrate the extent to which each parameter affects the equilibrium wage-setting mechanism in the high school and college sectors. For each parameter in the table, a

Table 4: Change in the average offered wage rate for women in response to parameter change

		High school graduates		**College graduates**	
		difference (%)	$\log(z)$ *change*	*difference (%)*	$\log(z)$ *change*
Human capital accum. rate	ρ	-1.2	-0.31	-27.3	-8.14
Separation rate	δ	8.0	0.49	58.2	3.51
Offers' arrival rate in *U*	λ_U	-26.6	3.55	-14.1	2.78
Offers' arrival rate in *E*	λ_E	-21.9	-1.77	-0.7	-0.06
PL exit rate in *OJ*	γ_2	-84.3	-0.18	-92.3	-0.32
PL exit rate in *NJ*	γ_3	-81.8	1.11	-95.8	3.69
OJ return rate	η	-21.1	-0.58	-13.9	-0.90

Notes: The table shows how women's log wage rates change upon equalizing each parameter to the level of men. The grayed columns show the average contribution of each parameter to the gap in log wage rates, $\log(z)$. Negative numbers imply an expansion of the gap. The percentages to the left of the average contributions to $\log(z)$ show the gender differences between the parameters as a percentage of men's.

positive (negative) number indicates the increase (decrease) to women's offered wage rate if women were to have the same parameter value as men in their respective sub-market. The table shows that steady-state, wage-setting gaps in the high school and college sectors are driven by different parameters. In the high school sector, λ_u has the largest impact — women's offered wage rates would increase substantially (by 3.5 log points) if non-employed women were to enjoy an offer arrival rate as high as that of non-employed men. In the college sector, human capital accumulation rate and separation rate both affect wage-setting substantially, although in opposite directions. College women would take a wage cut of 8.1 log points in exchange for higher future wage growth with men's ρ; and college women's wage offer would increase by 3.5 log points if their quit rate δ were reduced to men's level.

Both high school and college wage offers are driven by fertility parameters in similar ways. If women in parental leave who rejoin the labor force in unemployment (in the *NJ* state) were to return to the labor market as fast as men, their average offered wage rates would increase by 1.1 and 3.7 log points in the high school and college sectors, respectively. Since at the baseline women in *NJ* state spend extensive amounts of time out of the market around childbirth, reducing this time to men's levels is a substantial improvement in labor market attachment and eventually in women's productivity, which is rewarded by the firms. Women who return to their old job (those in the *OJ* state) spend such little time in parental leave that equalizing γ_2 across genders does not generate sizable responses from the firm's side. However, if a larger proportion of women were able to return to their old jobs after parental leave, then women in both the high school and college groups would accept a wage cut (of 0.6 and 0.9 log points). This is because having a higher chance to retain a job after having a child makes employment relatively more attractive, so women would lower their reservation rates.

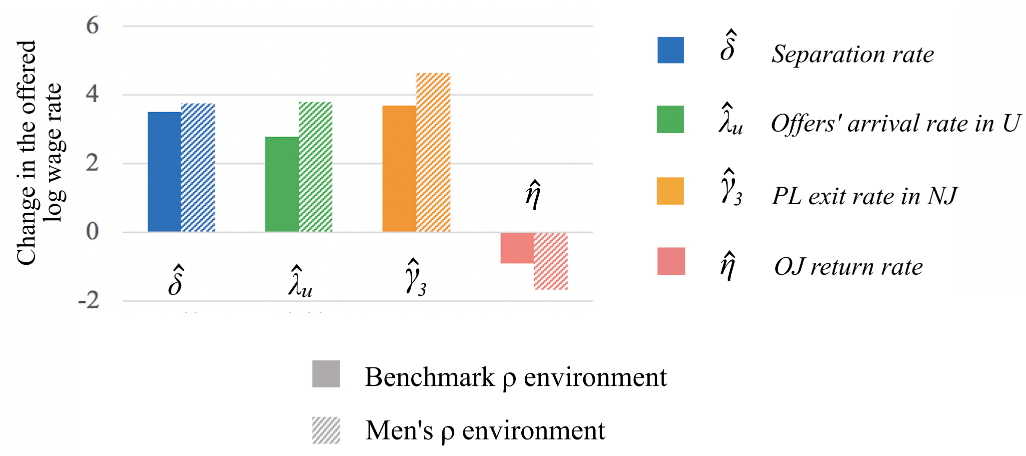
Intuitively, these endogenous wage effects are driven by both employers' profit motives and workers' reservation values. Employers reward worker attributes that lead to higher expected profits in equilibrium, and workers adjust their wage cutoffs based on future job prospects. For example, women's high separation rates imply short match durations and low expected match profits, so the forces of competition will make the employer discount offered wage rates for women as compared to men. Also, the low job arrival rates that women face in non-employment make them more willing to accept lower wage offers compared to men, as they anticipate less frequent job opportunities or engage in less intense job search than men.

The equilibrium wage discounts toward women might be exacerbated in work environments where human capital accumulation rate is high. Figure 7 shows the interactions between ρ and other parameters in determining offered wage rates, where we contrast the effects of the parameters in low- versus high-ρ environments. For example, college women would face an increase in wage offers of 2.8 log points if offers arrival rates λ_u were increased to men's level (as illustrated in Table 4). This increase in wage offers would become 3.8 log points in a high-ρ environment (almost 40% higher), because the benefits of a higher job arrival rate are greater when there is more learning on the job. Similarly, the wage effects of δ and γ_3 would also be more pronounced in high-ρ environments, because more stable employment and stronger labor market attachment become more valuable when productivity grows fast on the job. Since the raw wage gap is about 23 log points for college group, these effects are non-negligible. The immediate implications are two-fold: first, turnover differences would have an especially detrimental effect on wage offers to women in work environments with more intensive human capital accumulation; second, policies improving labor market attachment of women would generate a higher boost to women's wages in such high-learning environments.

An increase in parameter η (the probability that a woman returns to her previous employer after having a child) is special since it widens the gap at the beginning, due to a strong reservation wage response of the unemployed. Here as well, this effect is almost doubled in a high-ρ setting, because women would decrease their reservation rates even more when skills grow fast on-the-job.

It is important to consider human capital dynamics when illustrating employers' wage-setting decisions, and we show that the role of turnover in the gender gap in equilibrium wage offers would be substantially under-estimated if the human capital mechanisms were missing.

Figure 7: *Average change in women's offered wage rate in low and high ρ environments*



Notes: The figure shows the average contribution of each parameter to the gap in wage rates offered. The benchmark human capital accumulation environment keeps ρ at its estimated level — so the bars depict the values of college graduates for the corresponding parameters in Table 4. The men's human capital accumulation environment increases ρ to level of men.

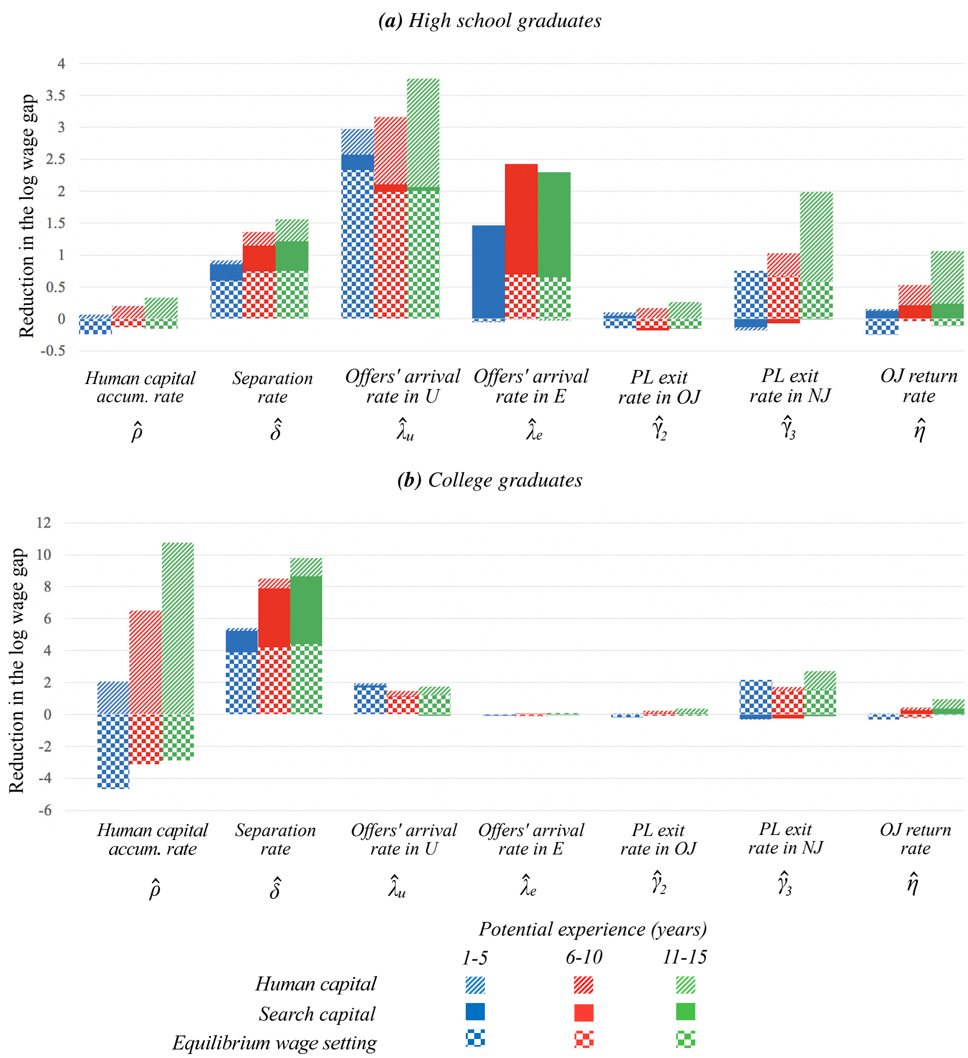
Bowlus (1997) computes firms' endogenous wage offers in a static setting using NLSY79 data as well. Focusing on wages on the first job, Bowlus (1997) finds that employers' wage-setting responses to turnover differences account for 20%–30% of the gender wage gap. In contrast, when employers take into account future dynamics of human capital evolution, they discount women's wages much more as they value stable employment more. We find that employers' responses to turnover differences account for 80% of the gender wage gap in our dynamic model. If we were to close down the human capital channel by assuming $\rho = 0$ and compute the counterfactual wage gap again, our model would produce an effect of turnover that is comparable to the estimate in Bowlus (1997) — about 20%. Therefore, the contribution of gender differences in turnover to the gender wage gap is sensitive to the assumption made about human capital dynamics. Whenever firms take dynamic considerations into account, they will penalize high turnover groups more heavily.

In the following section, we explore how these differences in equilibrium wage offers — wage ladders — combine with the differences in the speed of climbing the ladder and in human capital accumulation and shape the gender gap over the life-cycle.

5.3 Evolution of gender wage gaps over the life-cycle

Recall that at each point in the life-cycle, workers' wages are a combination of the current wage rate drawn from the steady-state offer distributions (outlined in Section 5.2) and the amount of human capital they have accumulated up to that point in their career. Each dimension of workers' attributes not only leads to differential wage offers by gender within the same job, it also affects the speed at which men and women advance through the job hierarchies and the amount of time they spend working and learning on the job. In this section, we describe how job-specific wage premia translate into the gender wage gap over the life-cycle, and how they compare with the other channels.

Figure 8: *The impact of each parameter on the life-cycle gender wage gap*



Notes: The figure shows the contribution of each parameter to the gender wage gap at different points of the life-cycle. Positive bars correspond to a reduction of the wage gap, and negative bars indicate an expansion. The striped portion of each bar shows the amount of the reduction (increase) of the wage gap attributed to the human capital channel, the solid portion represents the search capital channel, and the checkered portion reflects firms' wage-setting channel.

Table 5: *Total effect of gender difference in each parameter on the life-cycle wage gap.*

		High school graduates	**College graduates**
Human capital accum. rate	ρ	0.03	2.89
Separation rate	δ	1.28	7.92
Offers' arrival rate in *U*	λ_U	3.30	1.71
Offers' arrival rate in *E*	λ_E	2.04	0.00
PL exit rate in *OJ*	γ_2	0.02	0.09
PL exit rate in *NJ*	γ_3	1.17	1.98
OJ return rate	η	0.45	0.27
Average log wage gap		26.99	23.11

Notes: The table shows the total effect of each parameter in the life-cycle wage gap in log points. The bottom row shows the average log wage gap at benchmark values of the parameters

Figure 8 shows the extent to which each parameter contributes to the gender wage gap at different points of the life-cycle. Correspondingly, Table 5 presents the reduction in the average life-cycle gender gap if women were to have men's parameters. The portion of each bar in striped color shows the change in the women's wages due to the human capital channel, the portion in solid color reflects the search capital channel, and the checkered portion reflects employers' wage-setting responses. Upward-pointing bars indicate the decrease in the gap (increase in women's wages).

For high school graduates, the life-cycle wage gap between men and women is driven mainly by gender differences in job search and fertility interruptions. The job-finding rate λ_u not only leads to a significant discount towards women in the wage-setting process but also hinders women's human capital accumulation relative to men, which becomes especially pronounced later in their careers. Overall, it generates around 12% of the gap over the life-cycle. After having children, high school women spend a much longer time in non-employment than men in the *NJ* state (governed by γ_3), and this also implies forgone human capital for women as well as lower wage rates offered by employers. The gender difference in on-the-job offer arrival rates λ_e is also an important driver of the gap in the high school group it accounts for 8% of the gap), because the lower job mobility of women prevents them from accumulating the same search capital as men (see solid bars in Figure 8). Therefore, policies that help women navigate better job opportunities can be an effective measure for this group. The higher separation rate δ of high school women contributes to the gap as well, through all three channels, but its effect is more moderate compared to the aforementioned parameters.

For college graduates, two forces stand out as the main drivers of the life-cycle gap. The first one is the higher separation rate of women δ, accounting for 34% of the gap. As a result of their unstable employment episodes, college women not only face a substantial penalty in wage offers from employers, but also tend to fall off the career ladder more often than men and often start from scratch in unemployment. Since much of the job exits of women can be attributed to family reasons, policies that allow women to keep their job throughout most demanding child rearing periods — such as more flexibility in the timing of work or in the amount of working hours — would be especially relevant. This is in line with the findings of Manning and Petrongolo (2008) who highlight that better jobs usually do not allow for part-time work, and the findings of Goldin (2014) who identified hours flexibility as a major remaining obstacle in the way of gender pay equality. The second important parameter that drives the life-cycle gap in the college group is the gender difference in estimated human capital accumulation rate ρ, which generates 13% of the gap. If women were to have a higher rate of human capital growth, they would be willing to accept lower starting wages and thus would face lower equilibrium offers; however, over the life-cycle they would have a dramatic increase in human capital that more than compensate for the decrease in wage rates, as shown by striped bars in Figure 8.The implication of this result is that policies that provide more training opportunities to women might have a somewhat negative effect on women's wages at younger ages (as women would be willing to pay for these better opportunities), but will induce a significant increase in women's wages later in their careers.

These results imply that for both high school and college graduates, focusing on the human capital channel alone would not be enough to close the gender wage gap. Women face a career cost of weaker employment attachment, but only a small part of it is due to forgone human capital gains during non-employment periods. The main negative impact of a less stable employment on women's wages comes from employers' offer responses in anticipation of employment interruptions, and this force is especially important for the gender gap in early career. It is important for policies to improve women's labor force attachment and mobility (i.e., by reducing their quit rates and increasing job-finding rates all employment states), because these policies will make employers change their expectations about men and women and offer similar piece rates across genders.

We show in Section 5.2 that firms' wage-setting responses to gender differences in turnover are magnified in work environments with more intensive learning on-the-job. Over the life-cycle, additional dynamic interactions emerge between turnover and human capital accumulation because improved employment stability has a stronger effect on wages when each additional day in employment results in more accumulated skills. To illustrate both the static and dynamic interactions, Figure 9 compares the changes in gender wage gaps in low- versus high-

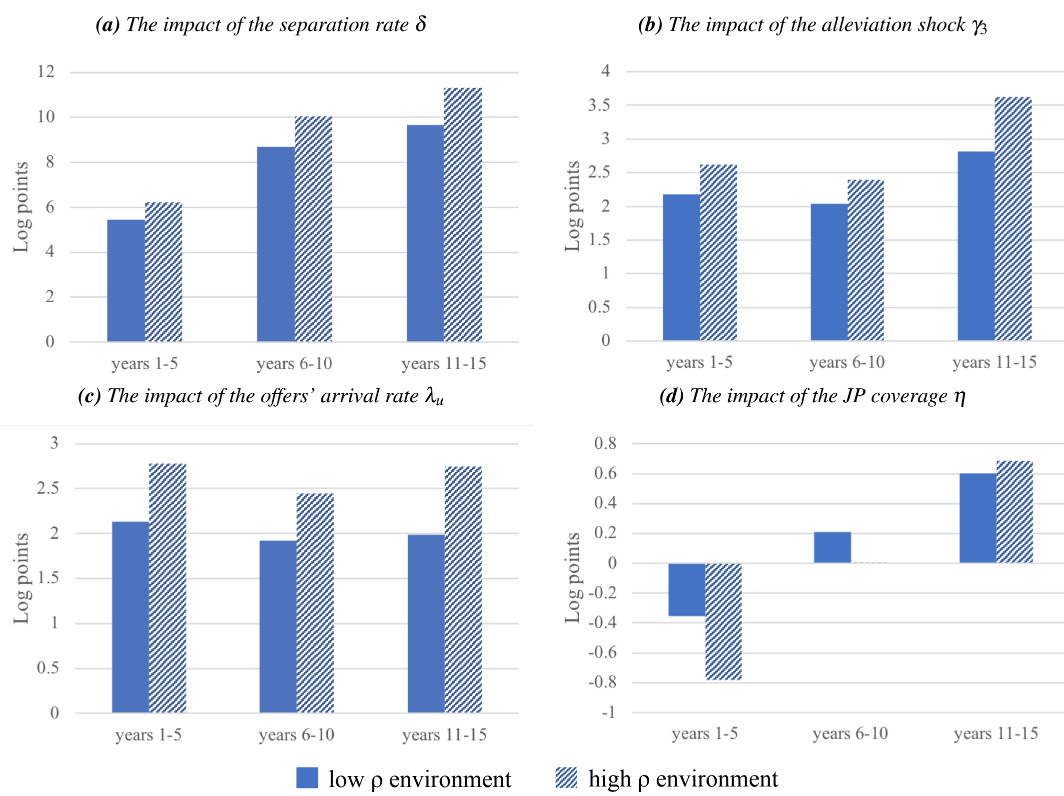
ρ environments as a result of a turnover parameter change, at various points in the life-cycle. Again, we use the estimates for the college sample for this exercise.

Figure 9 shows that the impact of turnover parameters depends on women's human capital accumulation rate. In early career, most of the gender wage gap is driven by the wage-setting channel (see Figure 5), so the interaction effects in years 1—5 look very similar to the static interactions shown in Section 5.2. In later career stages, human capital accumulation starts to play a bigger role in wages as a high-ρ environment reinforces the wage gains from improved stability.This is evident when there is a decrease in δ, or an increase in γ_3 or λ_u, as the difference between the striped and solid bars gets bigger in years 11–15. Interestingly, even though an increase in the return probability η initially leads to lower wages for women (as they are willing to pay for a greater chance to return to previous employers after parental leave), the effects are reversed later in the life-cycle as more women are able to accumulate skills in a more stable employment after childbirth, and these effects are again magnified in a high-learning environment.

An alternative way to illustrate the magnitude of the interactions is to look at the combined effect of the differences in turnover parameters and human capital accumulation rate ρ in contrast to their separate effects. We find that the separate effects of turnover differences and ρ on the average life-cycle gap are 13 and 2 log points, respectively. The combined effect of both these gender differences is, however, 18 log points — almost 20% higher than the sum of separate effects, suggesting substantial interactions between human capital accumulation and turnover.

The main conclusion from our interactions analysis is that the importance of the gender differences in labor market turnover for the life-cycle gender wage gap can not be analyzed separately from human capital dynamics. These interactions are important for policies that target both turnover and on-the-job training, as well as for policies that are implemented in specific labor market segments, in particular industries or occupations. For example, the impact of a job placement program for women would be different in occupations with high and low human capital accumulation rates. In high-growth environments, policies improving women's employment stability would be more efficient in reducing gender wage disparities.

Figure 9: *Turnover effects in high- and low- human capital accumulation environments*



Notes: The figure shows the contribution of each parameter to the gender wage gap at different points of the life-cycle. Positive bars correspond to a reduction of the wage gap, and negative bars indicate an expansion, in log points.

6 Conclusion

This paper analyzes the gender wage gap over the life-cycle distinguishing between the human capital and frictional components of the gap, while accounting for the equilibrium response of firms to the differences in labor market behaviors between men and women.

We find that the life-cycle wage gap is driven by different forces for high school and college graduates. For the former, firm-side differences in job productivities are a major factor, whereas for the latter human capital accumulation gap plays a big role. However, in both groups the differential wage rates that employers set for men and women are an important source of the gender wage disparities, accounting for around one-third of the gap. Although the discriminatory wage-setting mechanism we consider is illegal, it is generally difficult to detect discrimination in practice because firms may find ways to circumvent such regulations. For example, given that productivity is unobserved, firms can feasibly claim that the women who are paid less are simply less productive. Alternatively, employers may relabel the job titles of men and women in order to make their occupations seem different on paper, or they may argue that the male employees are more at risk of being poached and need to be paid more to stay. It is thus crucial to have a structural framework that separates unobserved productivity differences from employers' wage-setting differences.

Although we consider the differential wage offers for men and women to be a result of rational and profit-maximizing behaviors of employers, we do not suggest we should accept these outcomes as a society. Employers might not easily deviate from such rational behaviors, but policies can have substantial impacts on individual labor market outcomes through employers' endogenous wage-setting decisions.

After having children, those women who do not (or cannot) return to their previous employers typically spend a long period in non-employment, and this leads to substantial gender gaps in endogenous wage offers from employers especially for the college group. Therefore, policies that shorten these fertility-related career interruptions can have a sizable effect on the life-cycle gender wage gap. Besides fertility parameters, the most effective policies to reduce the wage gap are those that improve women's labor market stability throughout the life-cycle. For college-educated women, equalizing the separation rate to that of men would close the gap by 34% on average over years 1 to 15 over the course of their careers. For high school graduates, equalizing the job-finding rate across genders would close the gap by 12% on average over the same period. The key insight of the model is that the significant impact of turnover differences on the gender wage gap is, to a large extent, generated by its interaction with human capital dynamics. The intuition is two-fold: first, career interruptions are more costly when one foregoes intensive skill accumulation. Second, employers penalize high turnover groups, and this penalty is higher when employment is associated with a fast increase in productivity. Not taking these dynamic interactions into account would underestimate the contribution of gender differences in turnover to the life-cycle gender wage gap.

Our analysis opens up a number of potentially important margins to take account of in future research on gender inequality. On the theoretical side, possible extensions of our model might consider endogenizing the firm decisions to promote workers, to provide job-protected parental leave, and to hire or lay off a man versus a woman. These are important areas for future studies of the gender gap, and our model is well equipped to answer these questions, especially with the availability of matched employer-employee data. On the empirical side, more work needs to be done to shed light on the role of interactions between turnover and human capital. For example, human capital environments might differ by occupation, part-time and full-time status, or coworkers' demographics. One challenge for future empirical work is to identify exogenous variations in turnover in these different environments, but descriptive work on the interaction effects will allow us to gain further insights into the implications for the gender wage gap .

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Appendix A. Details of the Data

A.1 Sample construction

As mentioned in Section 2, we restrict the sample to the "Non-black, non-Hispanic" sample. We further restrict the sample to contain only individuals that had their first child after leaving full time education and drop those who have not worked at all in the 15 years after school.

We define potential experience starting from the year the person leaves full-time education — that is, potential experience equals the age of the individual minus total years of schooling minus 6, — and focus on the first 15 years of potential experience so we use the years 1979 to 2006.

We consider a person to be *employed* in a particular week if she is associated with an employer in that week , and the wage data is not missing. We consider a person to be *non-employed* if she is either unemployed, has no employment information, is "associated with employer, but dates missing," or if she is out of the labor force, or as the model does not distinguish between these two states.

For each week of potential experience we compute the number of people that are employed, non-employed, and the number of those who make transitions and the week after are in a different employment state or job from this week's. In particular, we consider three types of transitions: job-to-job, non-employment to employment (*UE*), and employment to non-employment (*EU*). Then we divide the number of people making a transition by the number of people in the pool to which they are transitioning to (employed or non-employed) in each week, to get weekly transition rates for each week; which we convert into monthly rates.

The UE and EU transitions are independent of experience in the model, therefore we compute the transition rates in each month of potential experience, where the latter is between 1 and 15 years, and take the average. The job-to-job transitions do depend on potential experience, through actual experience — a higher actual experience implies a lower chance of getting an even better offer. As specified in Section D.1, the model allows to obtain a closed-form expression for the job-to-job transition rate at each level of actual experience. The counterpart in the data is computed by weeks, then converted to months of actual experience and then averaged over 10 years of actual experience.

A.2 FMLA

In the U.S., federally mandated maternity leave was only introduced by the Family and Medical Leave Act (FMLA) in 1993, which provides up to 12 weeks of unpaid, job-protected leave to workers in companies with 50 employees or more. Prior to FMLA 1993, maternity leave coverage was governed by state laws, collective bargaining agreements and the goodwill of employers.[15] The data in Waldfogel (1999) show that no more than 40% of employees in medium to large firms[16] (and no more than 20% in small firms) were eligible to any form of maternity leave prior to 1993.

Out of those individuals who have children in our NLSY79 sample, 60% of them had their first child before 1988 and 86% before 1993. Given that the average number of children one has is close to 1 in our sample, we do not exploit the introduction of FMLA to analyze the effect of job protected maternity leave policies on employment with our sample. However, of those women who were working prior to childbirth, about 65.7% of them took maternity leave, and about 61.4% of those who were on leave went back to work within a year, mostly to the same employers. Therefore, we incorporate job protected maternity leave into our framework.

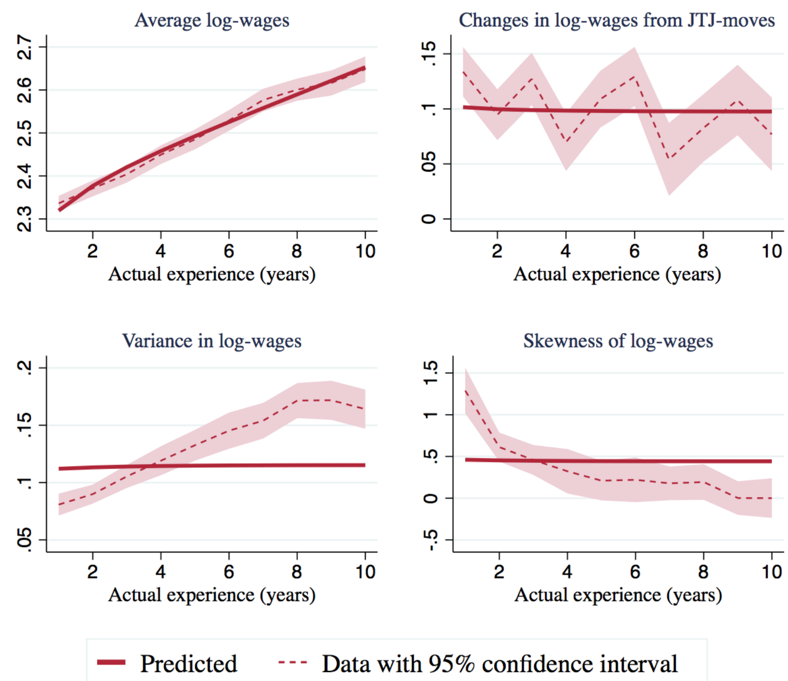
[15] Only six states (California, Connecticut, Massachusetts, Minnesota, Rhode Island, and Washington) required at least some private sector employers to offer maternity leave coverage prior to 1988. See more details about US maternity leave policies in Berger and Waldfogel (2004).

[16] These are firms with more than 100 employees. Small firms, instead, are firms with less than 100 employees.

Appendix B. Details of the Results

Figure B.1: *Fit of the targeted moments in GMM estimation for women*

(a) *High school graduates*



(b) *College graduates*

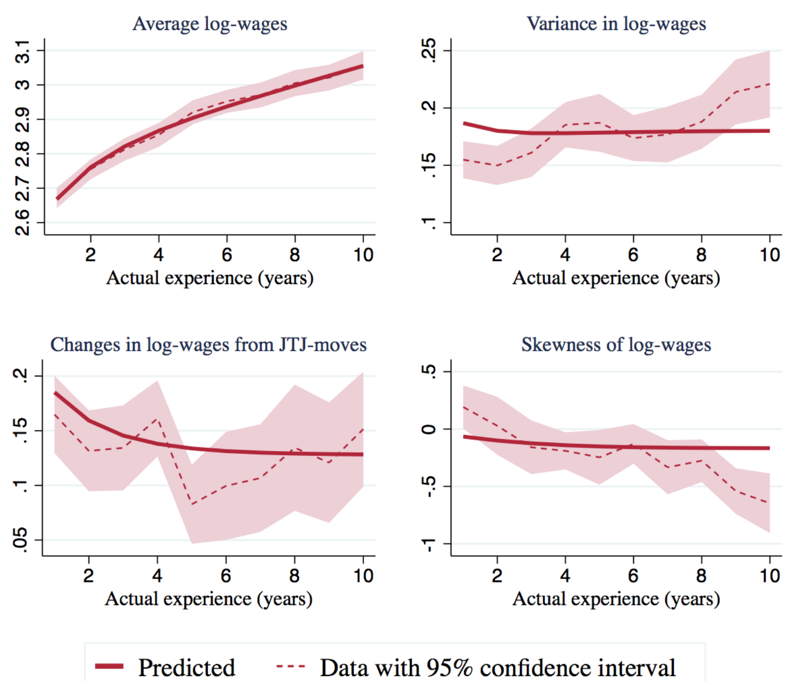
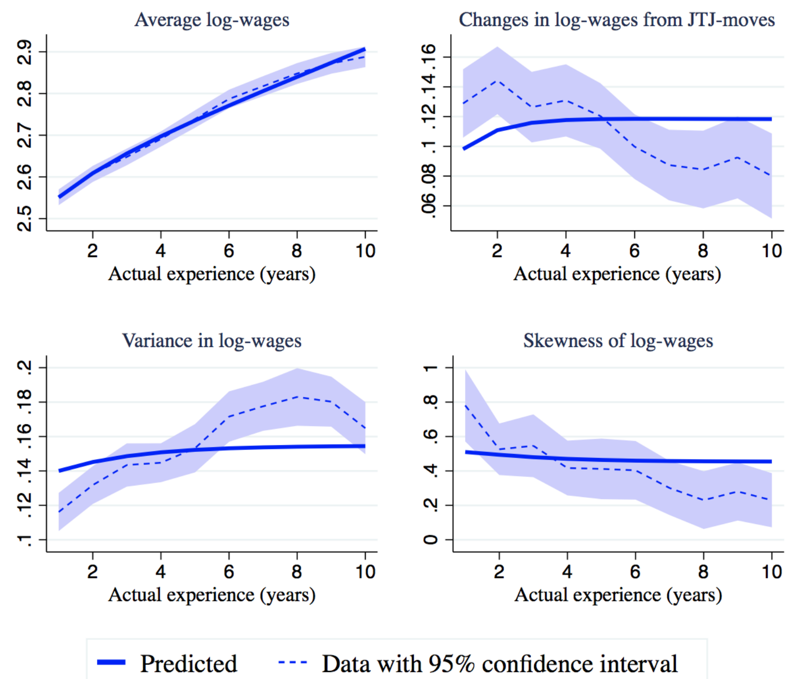
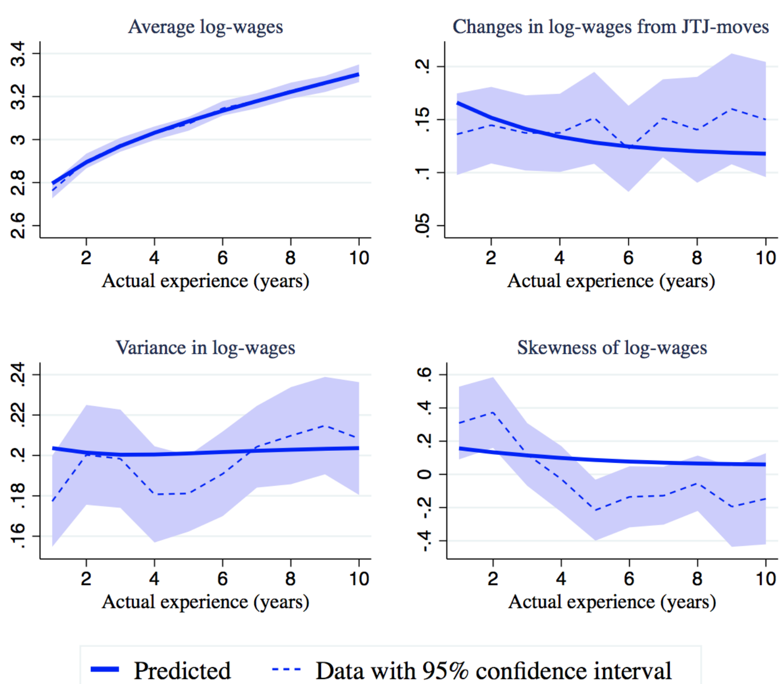


Figure B.2: *Fit of the targeted moments in GMM estimation for men*

(a) *High school graduates*



(b) *College graduates*



Appendix C. Details and Derivations of the Model *(For Online Publication)*

In this appendix, we show the properties of the model described in Section 3.

C.1 Linearity of the Value Functions

The productivity y of a worker with initial ability $\varepsilon \sim A(\varepsilon)$, can be expressed as a product of two components, $y = \varepsilon e^{\rho x}$. Therefore, when the worker is employed, $\partial y / \partial t = \rho y$. The dynamic component in the value function of employed workers is given by

$$\frac{\partial V(y,z)}{\partial t} = \frac{\partial V(y,z)}{\partial y} \rho y. \tag{14}$$

An important feature of equation (14) is that the dynamic component is proportional to the worker's productivity y.

Recall that the flow utilities in employment and unemployment — by and zy, — are linear in y. Combining (2) with (5) and (5) with (3), we see that the value functions themselves are linear in y and can be expressed as

$$\begin{aligned} U(y) &= \alpha^U y, \\ V(y,z) &= \alpha^E(z) y, \\ W^{OP}(y,z) &= \alpha^{OP}(z) y, \text{ and} \\ W^{NP}(y) &= \alpha^{NP} y, \end{aligned}$$

where α^U and α^{NP} are numbers and $\alpha^E(z)$, $\alpha^{OP}(z)$ are functions of z which are determined by (15), (16), (17), and (18) below.

C.2 Derivations: Worker's Side

In this section, we provide the proof of Proposition 1, which we restate below.

Proposition 1 *For a fixed $F(\cdot)$ with bounded and non-negative support, optimal job search implies that all unemployed workers have the same reservation cutoff z^R, which exists, is unique* *and is implicitly defined by*

$$\zeta_1\left(z^R-b\right)+\frac{(r+\phi)\zeta_2}{\lambda_u}(b^{out}-b)+\rho\left(b+\frac{\gamma_1}{r+\phi+\gamma_3}b^{out}\right)$$
$$=\left[\zeta_1(\lambda_u-\lambda_e)-\rho\lambda_u+(r+\phi)\zeta_2\right]\int_{z^R}^{\bar{z}}\frac{\overline{F}(z)}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}dz,$$

where $\zeta_1=r+\phi+\gamma_1-\frac{\gamma_1\gamma_3}{r+\phi+\gamma_3}$ *and* $\zeta_2=\frac{\lambda_u\gamma_1\eta(\gamma_3-\gamma_2)}{(r+\phi+\gamma_3)(r+\phi+\gamma_1+\gamma_2)}$.

Proof. The separable forms of the value functions (see Appendix C.1) imply we can simplify the workers' value functions (2), (3), (4) and (5) into expressions below,

$$(r+\phi)\alpha^U=b+\lambda_u\int_{z^R}^{\bar{z}}(\alpha^E(z)-\alpha^U)dF(z')+\gamma_1(\alpha^{NP}-\alpha^U), \tag{15}$$

$$(r+\phi)\alpha^E(z)=z+\rho\alpha^E(z)+\lambda_e\int_{z}^{\bar{z}}(\alpha^E(z')-\alpha^E(z))dF(z') \tag{16}$$
$$+\gamma_1(\eta\alpha^{OP}(z)+(1-\eta)\alpha^{NP}-\alpha^E(z))+\delta\left(\alpha^U-\alpha^E(z)\right),$$

$$(r+\phi)\alpha^{NP}=b^{out}+\gamma_3(\alpha^U-\alpha^{NP}), \tag{17}$$

$$(r+\phi)\alpha^{OP}(z)=b^{out}+\gamma_2(\alpha^E(z)-\alpha^{OP}(z))+\gamma_1(\alpha^{NP}-\alpha^{OP}(z)) \tag{18}$$

Differentiating (16) and (18) with respect to z yields the following ordinary differential equation on $\alpha^E(z)$:

$$\frac{d\alpha^E(z)}{dz}=\frac{1}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}. \tag{19}$$

With the boundary condition

$$\alpha^E(\bar{z})=\frac{\bar{z}+\frac{\gamma_1 b^{out}}{r+\phi+\gamma_2}+\left[\frac{\gamma_1\gamma_2[\gamma_1+\gamma_3+(1-\eta)(r+\phi+\gamma_2)]}{(r+\phi+\gamma_2)(r+\phi+\gamma_1+\gamma_2)}+\delta\right]\alpha^U}{r+\phi+\gamma_1+\delta-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}},$$

obtained by evaluating (16) and (18) at $\bar{z}$ and combining it with equation (17). Given α^U, the solution to this equation exists and is unique. Furthermore, given α^U, equation (17) solves for α^{NP}. Then, given $\alpha^E(z)$ and α^{NP}, equation (18) solves for $\alpha^{OP}(z)$. Finally, α^U and z^R satisfy the following two equations:

$$\left[\zeta_1(\lambda_u-\lambda_e)-\rho\lambda_u+(r+\phi)\zeta_2\right]\alpha^U=\lambda_u z^R-\lambda_e b+\left[\zeta_2+\frac{\gamma_1(\lambda_u-\lambda_e)}{r+\phi+\gamma_3}\right]b^{out}, \tag{20}$$

and

$$\zeta_1\alpha^U=b+\frac{\gamma_1}{r+\phi+\gamma_3}b^{out}+\lambda_u\int_{z^R}^{\bar{z}}\frac{\overline{F}(z)}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma 2}}dz. \tag{21}$$

where $\zeta_1=r+\phi+\gamma_1-\frac{\gamma_1\gamma_3}{r+\phi+\gamma_3}$ and $\zeta_2=\frac{\lambda_u\gamma_1\eta(\gamma_3-\gamma_2)}{(r+\phi+\gamma_3)(r+\phi+\gamma_1+\gamma_2)}$. Equation (20) is obtained by evaluating (16) at $z=z^R$, using that $\alpha^E(z^R)=\alpha^U$, and combining this with equation (15). Equation (21) is obtained by integrating (15) by parts. Finally, equations (20) and (21) can be combined into the following implicit equation on z^R:

$$\begin{aligned}\zeta_1\left(z^R-b\right)+\frac{(r+\phi)\zeta_2}{\lambda_u}(b^{out}-b)+\rho\left(b+\frac{\gamma_1}{r+\phi+\gamma_3}b^{out}\right)&\\ =\left[\zeta_1(\lambda_u-\lambda_e)-\rho\lambda_u+(r+\phi)\zeta_2\right]\int_{z^R}^{\bar{z}}\frac{\overline{F}(z)}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}dz.&\end{aligned} \tag{22}$$

The left-hand side of the equation above is monotonically increasing in z^R, while the left-hand side is monotonically decreasing in z^R. When $z^R=\bar{z}$, the left-hand side is positive, while the right-hand-side is 0. Therefore, there exists a unique $z^R<\bar{z}$ satisfying equation (22) above. This completes the proof. □

C.3 Characterization of Steady-State Measures and Distributions

?? in the text, which is restated below, characterizes the steady-state pools and distributions, for any given distribution of offers $F(z)$.

Proposition 2 *In steady state, for a given distribution of offers $F(z)$, the joint distribution of experiences and wage rates among the employed $H(x,z)$, and the distribution of experiences among the unemployed $N(x)$, are such that:*

i) $H(x,z)=\frac{m_U}{m_E}\lambda_u F(z)\left(\frac{1}{s(z)}\left(1-e^{-s(z)x}\right)-\left(1-\frac{R_1}{\lambda_U}\frac{m_E}{m_U}\right)\frac{1}{s(z)-R_1}\left(e^{-R_1x}-e^{-s(z)x}\right)\right)$ *where* $s(z)=q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}$, $\frac{m_E}{m_U}=\frac{\lambda_U}{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{phi+\gamma_1+\gamma_2}}$, $R_1=\frac{\phi\lambda_U(\phi+\gamma_3)}{m_E(\phi(\phi+\gamma_1+\gamma_3)+\lambda_U(\phi+\gamma_3))}$,

$m_U = \frac{(\phi+\gamma_3)X}{(\phi+\gamma_1+\gamma_3)(X+\lambda_U)+\frac{\eta\lambda_U\gamma_1(\gamma_3-\gamma_2)}{\phi+\gamma_1+\gamma 2}}$, *and* $X = \phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}$.

ii) $N(x) = 1-\left(1-\frac{\zeta_3}{\lambda_U}\frac{m_E}{m_U}\right)e^{-\zeta_3 x}$, *where* ζ_3 *is given by*

$$\zeta_3 = \frac{\phi(\phi+\gamma_3)\lambda_u}{[\phi(\phi+\gamma_1+\gamma_3)+\lambda_u(\phi+\gamma_3)]\, m_E}. \tag{23}$$

Proof. The steady-state requires that all the pools and the distributions are constant over time, which means that the following system of equations must hold:

i) Workers are in one of four states while in the labor market

$m_U + m_E + m_{OP} + m_{NP} = 1$,

ii) The flows into and out of the pool *OP* balance

$\eta\gamma_1 m_E = (\phi+\gamma_1+\gamma_2)\, m_{OP}$,

iii) The flows into and out of the employed pool balance

$\lambda_u m_U + \gamma_2 m_{OP} = (\phi+\delta+\gamma_1)\, m_E$, and

iv) The flows into and out of unemployed pool balance

$\phi+\delta\, m_E + \gamma_3 m_{NP} = (\phi+\gamma_1+\lambda_u)\, m_U$

v) The flows into and out of unemployed pool with experience below *x* balance

$\phi+\delta\, m_E H(x) + \gamma_3 m_{NP} N^{NP}(x) = (\phi+\gamma_1+\lambda_u)\, m_U N(x)$,

vi) The flows into and out of employed pool with experience below *x* balance

$\lambda_u m_U N(x) + \gamma_2 m_{OP} N^{OP}(x) = (\phi+\delta+\gamma_1)\, m_E H(x) + m_E \frac{dH(x)}{dx}$,

vii) The flows into and out of *OP*-pool with experience below *x* balance

$\eta\gamma_1 m_E H(x) = (\phi+\gamma_1+\gamma_2)\, m_{OP} N^{OP}(x)$,

viii) The flows into and out of *NP* - pool with experience below *x* balance

$\gamma_1 m_U N(x) + (1-\eta)\gamma_1 m_E H(x) + \gamma_1 m_{OP} N^{OP}(x) = (\phi+\gamma_3)\, m_{NP} N^{NP}(x)$, and

ix) The flows into and out of employed pool with experience below x and wage rate below z balance
$\lambda_u m_U N(x)F(z) + \gamma_2 m_{OP} H^{OP}(x,z) = q(z) m_E H(x,z) + m_E \frac{dH(x,z)}{dx}$.

x) The flows into and out of OP-pool with experience below x and wage rate below z balance
$\gamma_1 \eta m_E H(x,z) = (\gamma_1 + \gamma_2 + \phi) m_{OP} H^{OP}(x,z)$

The first four equations *(i)-(iv)* in the system above solve for the four unknowns m_U, m_E, m_{OP}, m_{NP}. Then, the remaining six equations *(v)-(x)* solve for the six unknowns $N(x)$, $H(x)$, $N^{OP}(x)$, $N^{NP}(x)$, $H(x,z)$, and $H^{OP}(x,z)$, such that the expressions in Proposition 2 are obtained. The derivations are tedious but straightforward and are available upon request. □

C.4 Derivations: Firm's Side

In this section, we provide the proof of Proposition 2. We also provide an expression for z^R in Proposition 5 and show that a steady-state market equilibrium exists and is unique in Theorem 1.

Lemma 1. *The steady-state profits of a firm with productivity p posting a wage offer z,*

i) can be expressed as:

$$\pi(z,p) = \frac{\zeta_4}{\left(q(z) - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \rho\right)^2}(p-z)$$

where

$$\zeta_4 = \frac{\widetilde{\varepsilon} m_U \lambda_u \zeta_3}{\zeta_3 - \rho}\left(\frac{\phi+\delta+\gamma_1 - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \rho}{\phi+\delta+\gamma_1 - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right)\left(\phi+\delta+\gamma_1 - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \rho + \lambda_e\right), \textit{and}$$

ii) the optimal wage policy is increasing in p so that more productive firms post higher wage offers.

Proof. First, using the results in Proposition 2 above, we have that:

$$\int_0^\infty e^{\rho x'} dN(x') = \frac{\zeta_3}{\zeta_3 - \rho}\left(\frac{\phi+\delta+\gamma_1 - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \rho}{\phi+\delta+\gamma_1 - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right),$$

and

$$\int_{z^R}^{z}\int_0^{\infty} e^{\rho x'} d^2H(x',z') = \frac{m_U}{m_E}\cdot\frac{\lambda_u F(z)}{q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}\left[1+\frac{n_2\rho}{(\zeta_3-\rho)}\right],$$

where $n_2 = 1-\frac{\zeta_4}{\lambda_u}\frac{m_E}{m_U}$. Using the above expressions we simplify equation (8) for y^{init} to:

$$y^{init}(z) = \frac{\widetilde{\varepsilon} m_U \lambda_u \zeta_3}{\zeta_3-\rho}\left(\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right)\left(\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho+\lambda_e}{q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}\right),$$

which can be expressed as $y^{init}(z) = \zeta_4/M(z)$, where

$$M(z) = q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho, \text{ and}$$
$$\zeta_4 = \frac{\widetilde{\varepsilon} m_U \lambda_u \zeta_3}{\zeta_3-\rho}\left(\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right)\left(\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho+\lambda_e\right).$$

Second, equation (9) simplifies to:

$$y^{acc}(z) = \frac{1}{\rho}\left[\frac{q(z)}{q(z)-\rho}-1\right]+\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\frac{y^{acc}(z)}{q(z)-\rho},$$

which yields $y^{acc}(z) = 1/M(z)$, so that

$$\pi(z,p) = y^{init}(z)\,y^{acc}(z)(p-z) = \frac{\zeta_6}{M(z)^2}(p-z).$$

Finally, since $\zeta_6/M(z)^2$ is monotonically increasing in z, it is straightforward to show that, in equilibrium, more productive firms post higher offers. This completes the proof of Lemma 1. □

Proposition 3. Given the reservation rate of the unemployed z^R, the optimal wage offer of a given firm with productivity p, $z = \xi(p)$, can be expressed as

$$\xi(p) = p - M(\xi(p))^2\int_{z^R}^{p}\frac{1}{M(\xi(p'))^2}dp', \tag{24}$$

where $M(\cdot)$ is defined as in the proof of Lemma 1 above.

Proof. By Lemma 1, for any $z \in \left[z^R,\bar{z}\right]$, $F(z) = F(\xi(p)) = \Gamma(p)$. Let the profits from posting an optimal offer $\xi(p)$, be denoted by $\pi^*(\xi(p))$. By the envelope theorem, $\frac{\partial\pi^*(\xi(p))}{\partial p} = \ell(\xi(p))$. Integrating back, and using that $\pi^*(\xi(\underline{p})) = (\underline{p} - z^R)\ell(z^R)$,

$$\pi^*(\xi(p)) = \int_{z^R}^{p} \ell(\xi(x))dx = \int_{z^R}^{p} \frac{\zeta_6}{M(\xi(x))^2}dx.$$

Note that $\pi^*(\xi(p)) = (p - \xi(p))\ell(\xi(p))$ implies that

$$\xi(p) = p - \frac{\pi^*(\xi(p))}{\ell(\xi(p))} = p - \frac{\int_{z^R}^{p} \frac{\zeta_6}{M(\xi(x))^2}dx}{\frac{\zeta_6}{M(\xi(p))^2}} = p - M(\xi(p))^2 \int_{z^R}^{p} \frac{1}{M(\xi(p'))^2}dp'. \tag{25}$$

The above equation gives the optimal wage policy of a firm with productivity p, given the reservation wage rate of workers, z^R. Notice that we should separately regard the case in which $z^R < \underline{p}$, so that

$$\xi(p) = p - \frac{\frac{(\underline{p}-z^R)}{M(\xi(\underline{p})^2} + \int_{\underline{p}}^{p} \frac{1}{M(\xi(x))^2}dx}{\frac{1}{M(\xi(p))^2}}, \tag{26}$$

and

$$M(\xi(\underline{p})) = \phi + \delta + \gamma_1 - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \rho + \lambda_e.$$

This completes the proof of Proposition 3. □

Proposition 4. *Given the optimal wage-setting function $\xi(p)$ optimal job search implies that z^R is implicitly defined by:*

$$\begin{aligned}
\tfrac{(\gamma_3-\gamma_2)\gamma_1\eta}{r+\phi+\gamma_1+\gamma_2}\left(b^{out}-b\right) = \left(b-z^R\right)(r+\phi+\gamma_1+\gamma_3) - \rho\frac{b(r+\phi+\gamma_3)+\gamma_1 b^{out}}{r+\phi} \\
+ \zeta_5\Bigg[\frac{\left(\underline{p}-z^R\right)}{M(\xi(\underline{p}))^2}\int_{\underline{p}}^{\overline{p}} \frac{(1-\Gamma(x))}{\left(q(\xi(x))+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\Psi(x)dx \\
+ \int_{\underline{p}}^{\overline{p}} \frac{(1-\Gamma(x))}{\left(q(\xi(x))+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\left(\int_{\underline{p}}^{x}\frac{1}{M(\xi(r))^2}dr\right)\Psi(x)dx\Bigg]
\end{aligned}$$

with $\zeta_5 = (\lambda_u - \lambda_e)(r+\phi+\gamma_1+\gamma_3) - \frac{\rho(r+\phi+\gamma_3)\lambda_u}{r+\phi} + \frac{(\gamma_3-\gamma_2)\eta\lambda_u\gamma_1}{r+\phi+\gamma_1+\gamma_2}$ and $\Psi(p) = 2\lambda_e\Gamma'(p)M(\xi(p))$.

Proof. We prove the proposition by combining the expression for $\xi(p)$ from equation (25) above, with equation (22) which yields,

$$\int_{z^R}^{\bar{z}} \frac{(1-F(z))}{\left(q(z)+r-\rho-\frac{\eta\cdot\gamma_1\cdot\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)} dz = \int_{\underline{p}}^{\overline{p}} \frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)} \xi'(x)dx.^{17} \tag{27}$$

Using the equation for optimal wage function (25), we find the derivative $\xi'(p)$, which is given by

$$\xi'(p) = \left(\frac{(\underline{p}-z^R)}{M(\xi(\underline{p}))^2} + \int_{\underline{p}}^{p} \frac{1}{M(\xi(x))^2} dx\right)\Psi(p). \tag{28}$$

Summing up using equation (22),

$$\frac{(\gamma_3-\gamma_2)\gamma_1\eta}{r+\phi+\gamma_1+\gamma_2}\left(b^{out}-b\right) = \left(b-z^R\right)(r+\phi+\gamma_1+\gamma_3) - \rho\frac{b(r+\phi+\gamma_3)+\gamma_1 b^{out}}{r+\phi} + \zeta_5 \int_{z^R}^{\bar{z}} \frac{\overline{F}(z)}{\left(q(z)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}.$$

Then, using equation (27),

$$\begin{aligned}\frac{(\gamma_3-\gamma_2)\gamma_1\eta}{r+\phi+\gamma_1+\gamma_2}\left(b^{out}-b\right) &= \left(b-z^R\right)(r+\phi+\gamma_1+\gamma_3) - \rho\frac{b(r+\phi+\gamma_3)+\gamma_1 b^{out}}{r+\phi} \\ &+\zeta_5\left[\frac{(\underline{p}-z^R)}{M(\xi(\underline{p}))^2}\int_{\underline{p}}^{\overline{p}} \frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\Psi(x)dx\right. \\ &\left.+\int_{\underline{p}}^{\overline{p}} \frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\left(\int_{\underline{p}}^{x}\frac{1}{M(\xi(r))^2}dr\right)\Psi(x)dx\right].\end{aligned}$$

□

Theorem 1. *For any $\rho > \phi$, a steady-state market equilibrium exists and is unique.*

Proof. Proposition 5 finds the optimal reservation cutoff z^R that is consistent with worker's and

[17] We change the variable of integration from z to p, and use the formula: $\int_{\phi(a)}^{\phi(b)} f(x)dx = \int_a^b f(\phi(t))\phi'(t)dt$.

firm's optimal decisions. As follows from Proposition 1, this cutoff is unique. Then, Proposition 4 defines firms' optimal wage-setting rule given the reservation wage, z^R, Proposition 3 establishes that the distribution of offers is equal to the distribution of firms' productivities, and Proposition 2 defines all the steady-state distributions, given the distribution of offers which are consistent with steady-state turnover. Therefore, the steady-state equilibrium exists and is unique. □

Appendix D. Details of Estimation *(For Online Publication)*

D.1 Exogenous parameters

First, the average number of children that an individual has over the course of 15 years in the labor market uniquely determines γ_1 in each gender-education subgroup.

Next, note that monthly transition probabilities — the probabilities to make a transition over the course of a month — and durations of different states can be expressed through the model Poisson rates parameters and the rate of job protection η.

In particular, the probability to move from unemployment to employment over the course of a month, D_{UtoE} is given by

$$D_{UtoE} = \frac{\lambda_u}{\phi + \gamma_1 + \lambda_u} \left(1 - e^{-(\phi+\gamma_1+\lambda_u)}\right). \tag{29}$$

Thus given ϕ, γ_1 and D_{UtoE} — which can be obtained from the data, — we can solve for λ_u.

A similar approach given ϕ and γ_1 yields δ using the probability to move from employment into unemployment over the course of a month, D_{EtoU},

$$D_{EtoU} = \frac{\delta}{\phi + \delta + \gamma_1} \left(1 - e^{-(\phi+\delta+\gamma_1)}\right). \tag{30}$$

and γ_2 from the average duration of the job protected maternity leave,

$$\mathbb{E}(JP \text{ duration}) = \frac{1}{\phi + \gamma_1 + \gamma_2}. \tag{31}$$

Then, given given ϕ, γ_1 and λ_u we solve for γ_3 using the average duration of a maternity career interruptions that started in unemployment, involved only one birth and ended in employment, $\mathbb{E}(NJP \text{ duration})$, which is given by

$$\mathbb{E}(NJP \text{ duration}) = \frac{1}{(\phi+\gamma_1+\gamma_3)} + \frac{1}{(\phi+\gamma_1+\lambda_u)}.$$

And given ϕ, γ_1 and γ_2, we solve for η using the share of workers observed returning to their previous employer after having a child given by,

$$\mathbb{P}(\text{Come back}) = \frac{\eta\gamma_2}{\phi+\gamma_1+\gamma_2}. \tag{32}$$

Getting at λ_e is not as straight forward but we can derive it from the data as follows.

First note that the probability that a job offering a wage rate z ends in a job-to-job transition after a duration of τ is given by

$$\mathbb{P}(\tau) = \lambda_e(1-F(z))\,e^{-\lambda_e(1-F(z))\tau}e^{-(\phi+\delta+\gamma_1)\tau}.$$

So the proportion of those who do a job-to-job transition from jobs paying z over one unit of time is given by,

$$D_{EtoE}(z) \quad = \quad \int_0^1 \mathbb{P}(\tau)d\tau = \frac{\lambda_e(1-F(z))}{q(z)}\left(1-e^{-(\phi+\delta+\gamma_1+\lambda_e(1-F(z)))}\right),$$

and, overall in the economy, the proportion of workers moving from one job to another at level of actual experience x is

$$D_{EtoE}|x = \int_{\underline{z}}^{\overline{z}} D_{EtoE}(z)dH(z|x), \tag{33}$$

where $H(z|x)$ is the distribution of accepted wage rates conditional on actual experiences.

Note that z enters $D_{EtoE}(z)$ only through $F(z)$ — i.e. we could re-write $D_{EtoE}(z)$ as a function $\tilde{D}_{EtoE}(F(z))$. The key feature that allows us to obtain an expression of λ_e that has a data-counterpart is that z enters $H(z|x)$ only through $F(z)$ as well. Thus $dH(z|x)$ is a function of parameters, $F(z)$ and it is proportional to $f(z)$, which allows for the integral to be solved for and does not depend on $F(z)$.[18] We derive the expression below, however, the intuition behind this is as follows. The transition rate from job-to-job depends on the *relative* ranking (say, percentile) of a current wage rate in the distribution of offers, $F(z)$ — the higher the percentile, the lower is the mass of attractive offers, and the lower is the chance to make a job-to-job transition. At the beginning of a career, or at any time when hired from non-employment, workers have an equal chance to get an offer from any percentile (a chance of 1/100 precisely), and when looked at some time afterwards, their current relative position in the distribution will only be a function of the speed of ascent (λ_e) and the intensities of events that disrupt the ascent (separations and child shocks). To sum up, the *shape* of F and its support have no bearing on the rate of job-to-job transitions since the latter only depends on the relative position (e.g. percentile) of the current wage rate in the distribution.

Formally, our expression for λ_e is derived as follows.

Let $\omega = \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}$, $R = \frac{\phi(\phi+\gamma_3)\lambda_u}{[\phi(\phi+\gamma_1+\gamma_3)+\lambda_u(\phi+\gamma_3)]m_E}$ and $n_2 = 1 - \frac{R}{\phi+\delta+\gamma_1-\omega}$. Then the distribution of wage rates conditional on actual experience levels is given by

$$H(z|x) = (\phi+\delta+\gamma_1-\omega)F(z)\left(\frac{1-e^{-s(z)x}}{s(z)} - \frac{n_2\,(e^{-Rx}-e^{-s(z)x})}{s(z)-R}\right)\Big/ H(x).$$

where $H(x) = 1-e^{-Rx}$ and $s(z) = q(z)-\omega$.

To algebraically show that (33) does not depend on $F(z)$, following Hornstein et al. (2011), consider the change of variable given by $t = F(z)$ so that $(F^{-1})'(t) = \frac{1}{f(z)}$. It follows that

$$\begin{aligned} dH(z|x) = \frac{(\phi+\delta+\gamma_1-\omega)}{H(x)}\Bigg[&\left(\frac{1-e^{-(\tilde{q}(t)-\omega)x}}{\tilde{q}(t)-\omega} - \frac{n_2\,(e^{-Rx}-e^{-(\tilde{q}(t)-\omega)x})}{\tilde{q}(t)-\omega-R}\right)\\ &-\lambda_e t\left(e^{(\tilde{q}(t)-\omega)x}\left\{\frac{-x(\tilde{q}(t)-\omega)+1}{(\tilde{q}(t)-\omega)^2} - n_2\frac{x(\tilde{q}(t)-\omega-R)+1}{(\tilde{q}(t)-\omega-R)^2}\right\}\right.\\ &\left.-\frac{1}{(\tilde{q}(t)-\omega)^2} - \frac{e^{-R}}{(\tilde{q}(t)-\omega-R)^2}\right)\Bigg]dt \end{aligned}$$

[18] By the second part of the fundamental theorem of calculus, the integral of $D_{EtoE}(z)dH(z|x) = \tilde{D}_{EtoE}(F(z))\tilde{H}(F(z)|x)f(z)dz$ is the difference between the anti-derivative of $\tilde{D}_{EtoE}(F(z))\tilde{H}(F(z)|x)f(z)dz$ — which does not depend on $F(z)$ — evaluated at $\bar{z}$ and at $\underline{z}$.

where $\tilde{q}(t) = \phi + \delta + \gamma_1 + \lambda_e(1-t)$.

Thus, under the proposed change of variables $t = F(z)$,

$$D_{EtoE}|x = \int_{\underline{z}}^{\bar{z}} \frac{\frac{\lambda_e(1-t)}{q(t)}\left(1-e^{-\tilde{q}(t)}\right)}{e^{-(\phi+\delta+\gamma_1-\omega)x} + \frac{n_2\left(Re^{-Rx}-(\phi+\delta+\gamma_1-\omega)e^{-(\phi+\delta+\gamma_1-\omega)x}\right)}{\phi+\delta+\gamma_1-\omega-R}}$$
$$\times\left[\left(e^{-(q(t)-\omega)x} + \frac{n_2\left(Re^{-Rx}-(\tilde{q}(t)-\omega)e^{-(\tilde{q}(t)-\omega)x}\right)}{\tilde{q}(t)-\omega-R}\right)\right.$$
$$+t\lambda_e\left(e^{-(q(t)-\omega)x}x + \frac{n_2 Re^{-Rx}}{(q(t)-\omega-R)^2} - \right.$$
$$\left.\left.-n_2 e^{-(\tilde{q}(t)-\omega)x}\left[\frac{(\tilde{q}(t)-\omega)\,x\,(\tilde{q}(t)-\omega-R)+R}{(\tilde{q}(t)-\omega-R)^2}\right]\right)\right]dt$$

which does not depend on F. Thus,

$$\text{Job Duration} \;=\; K\left[\begin{array}{c}\left[\frac{\phi+\gamma_1+\gamma_2}{\eta\gamma_1\gamma_2}\right]^2\frac{1}{\lambda_e}\ln\left(\frac{\phi+\delta+\gamma_1+\lambda_e}{\phi+\delta+\gamma_1}\,\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}{\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right)\\ +\frac{\phi+\gamma_1+\gamma_2}{\eta\gamma_1\gamma_2}\frac{1}{\left(\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)\left(\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)}\end{array}\right] \tag{34}$$

where $K = \left(\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)\left(\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)$.

All the derivations above are based on the competing risk structure of the model — duration of each spell is defined by the terminating event that occurs first (for example, the transition from unemployment to employment will only happen if the job offer event λ_u will occur before other competing events that terminate an unemployment spell, such as birth of a child γ_1 or permanent exit ϕ). The elegant mathematics of the Poisson processes allows to concisely characterize the respective probabilities.

In this way, we have a system of six equations in six unknowns $\{\gamma_2, \gamma_3, \lambda_u, \lambda_e, \delta, \eta\}$, linking the unknown model parameters with turnover rates between employment and unemployment, durations of protected and unprotected parental leaves, average job-to-job transition rate and the share of workers coming back to their old employer after parental leave. We solve the system and with the parameters in hand, proceed to the second stage of the estimation.

D.2 Joint estimation via GMM

In this section we briefly summarize the steps we follow to estimate the parameters $\beta = (\underline{p}, \overline{p}, \kappa_1, \kappa_2, \rho, \alpha_1, \alpha_2, b)'$ via GMM given the Poisson rates $\delta, \gamma_1, \gamma_2, \gamma_3, \lambda_e, \lambda_u$ — which are estimated from turnover and fertility data as outlined above.

In order to construct the GMM objective function,

$$\hat{\beta} = \arg\min_{\beta} \left(\frac{1}{N} \sum_{i=1}^{N} f(X_i, \beta) \right)' W \left(\frac{1}{N} \sum_{i=1}^{N} f(X_i, \beta) \right),$$

we compute the model implied moments that we target (see Section 4.1).

Recall that the equilibrium objects of our model consist of the tuple $\{z^R,\ m_E,\ m_U,\ m_{JP},\ m_{NJP},\ H(\cdot),\ N(\cdot),\ N^{JP}(\cdot),\ N^{NJP}(\cdot),\ H(\cdot,\cdot),\ H^{JP}(\cdot,\cdot),\ F(\cdot),\ \xi(p)\}$. These objects are needed to compute moments such as the model-implied average log-wages, which are included in our set of targeted moments as described in Section 4.1. Our model lends itself for GMM estimation as its tractability allow us to solve for all the equilibrium objects given a value for β as detailed in Section D.3 below.

D.3 Analytical solutions of target moments

Recall that log-wages in our model are given by

$$\log w_i = \log \varepsilon_i + \rho x_i + \log z_i$$

In Sections D.3.1 to D.3.6 we detail how we derive the model implied moments we use for estimation.

D.3.1 Mean log wage by actual experience

Mean log-wages conditional on actual experience are given by

$$\mathbb{E}(\log w|x) = \rho x + \mathbb{E}(\log z|x) + \underbrace{\mathbb{E}(\log \varepsilon_i|x)}_{\widetilde{\log \varepsilon}} = \rho x + \log z^R + \int_{z^R}^{\bar{z}} \frac{1 - H(z|x)}{z} dz + \widetilde{\log \varepsilon}.$$

D.3.2 Variance of log wage by actual experience

The variance of log-wages conditional on actual experience, x, is given by

$$\begin{aligned}
Var(\log w|x) &= \mathbb{E}[(\log w - \mathbb{E}(\log w|x))^2|x] \\
&= \mathbb{E}[(\log \varepsilon + \rho x + \log z - \left(\rho x + \mathbb{E}(\log z|x) + \widetilde{\log \varepsilon}\right))^2|x] \\
&= Var(\log \varepsilon) + \int_{z^R}^{\bar{z}} \left(\log z - \log z^R - \int_{z^R}^{\bar{z}} \frac{1-H(z'|x)}{z'} dz'\right)^2 dH(z|x),
\end{aligned}$$

The derivative of the conditional distribution $H(z|x)$ with respect to the wage rate z is given by,

$$\frac{dH(z|x)}{dz} = \frac{f(z)}{e^{-(q(\bar{z})-\omega)x} + \frac{n_2\left(R_1 e^{-R_1 x} - (q(\bar{z})-\omega)e^{-(q(\bar{z})-\omega)x}\right)}{q(\bar{z})-\omega-R_1}} \times \left[\begin{array}{c} e^{-(q(z)-\omega)x} + \frac{n_2 R_1 e^{-R_1 x}}{q(z)-\omega-R_1} - \frac{n_2 e^{-(q(z)-\omega)x}}{1-\frac{R_1}{(q(z)-\omega)}} \\ +\lambda_e F(z) \left(\begin{array}{c} e^{-(q(z)-\omega)x} x + \frac{n_2 R_1 e^{-R_1 x}}{(q(z)-\omega-R_1)^2} - \\ - \frac{n_2 e^{-(q(z)-\omega)x}\left(x\left(q(z)-\omega\right)\left(q(z)-\omega-R_1\right)+R_1\right)}{[q(z)-\omega-R_1]^2} \end{array} \right) \end{array} \right], \tag{35}$$

where to avoid the numerical computation of the density $f(z)$ we use the equilibrium mapping between z and p, namely $F(z) = F(\xi(p)) = \Gamma(p)$, which implies that $f(z) = \frac{dF(z)}{dz} = \frac{\Gamma'(p)}{\xi'(p)}\Big|_{z=\xi(p)}$. Note that from the equilibrium solution we have an analytical expression for $\xi'(p)$ (see equation (28)). It follows that,

$$f(z) = \frac{\Gamma'(p)}{\left(\frac{(\underline{p}-z^R)}{M(\xi(\underline{p}))^2} + \int_{\underline{p}}^{p} \frac{1}{M(\xi(x))^2} dx\right)\Psi(p)} = \frac{1}{\left(\frac{(\underline{p}-z^R)}{M(\xi(\underline{p}))^2} + \int_{\underline{p}}^{p} \frac{1}{M(\xi(x))^2} dx\right) \times 2\lambda_e M(p)}, \text{ and}$$

$$f(z^R) = \frac{\Gamma'(\underline{p})}{\xi'(\underline{p})}\Big|_{z^R=\xi(\underline{p})} = \frac{1}{\left(\frac{(\underline{p}-z^R)}{M(\xi(\underline{p}))^2}\right) \times 2\lambda_e M(\xi(\underline{p}))}.$$

where the numerator cancels out as $\Psi(p) = 2\lambda_e \Gamma'(p) M(\xi(p))$.

D.3.3 Mean log-wage change upon job-to-job transition by actual experience

A log-wage jump upon a job-to-job transition at actual experience x is given by,

$$\left(\log w_i' - \log w_i\right)|x_i = \log \varepsilon_i + \rho x_i + \log z_i' - \log \varepsilon_i - \rho x_i - \log z_i = \log z_i' - \log z_i$$

The average wage jump upon a job-to-job transition, conditional on x, is equal to

$$\mathbb{E}(\triangle \log w|x) = \int_{zR}^{\overline{z}} \left(\mathbb{E}(\log z'|z' > z) - \log z\right) dH(z|x)$$

where $\mathbb{E}(\log z'|z' > z)$ is the average offer conditional that it is higher than the current wage rate z. This average offer depends on the distribution of offers $F(\cdot)$ and the current wage rate z,

$$\mathbb{E}(\log z'|z' > z) = \int_{z}^{\overline{z}} \frac{\log z'}{1-F(z)} dF(z')$$

so that

$$\mathbb{E}(\triangle \log w|x) = \int_{zR}^{\overline{z}} \left(\frac{\int_z^{\overline{z}} \log z' dF(z')}{1-F(z)} - \log z \right) dH(z|x).$$

Note that the numerator of the integrand above is given by,

$$\int_{z}^{\overline{z}} \log z' dF(z') = \log z' F(z')\Big|_z^{\overline{z}} - \int_z^{\overline{z}} F(z') d\log z' = \log(\overline{z}) - F(z)\log z - \int_z^{\overline{z}} \frac{F(z')}{z'} dz'$$

and hence

$$\begin{aligned}
\mathbb{E}(\triangle \log w|x) &= \int_{zR}^{\overline{z}} \left(\frac{\log(\overline{z}) - F(z)\log z - \int_z^{\overline{z}} \frac{F(z')}{z'} dz'}{1-F(z)} - \log z \right) dH(z|x) \\
&= \int_{zR}^{\overline{z}} \left(\frac{\int_z^{\overline{z}} \frac{1-F(z')}{z'} dz'}{1-F(z)} \right) dH(z|x).
\end{aligned}$$

D.3.4 Skewness

Let us denote the skewness of log-wages at actual experience x by $S(\log w|x)$. Then,

$$S(\log w|x) = \mathbb{E}\left[\left(\frac{\log w - \mathbb{E}(\log w|x)}{(Var(\log w|x))^{0.5}} \right)^3 |x \right]$$

$$= \frac{\mathbb{E}\left(\left[\log\varepsilon+\rho x+\log z-(\rho x+\mathbb{E}(\log z|x)+\mathbb{E}(\log\varepsilon))\right]^3\Big|x\right)}{(Var(\log w|x))^{3/2}}$$

$$= \frac{\int_{z^R}^{\bar{z}}\left(\log z-\log z^R-\int_{z^R}^{\bar{z}}\frac{1-H(z|x)}{z}dz\right)^3 dH(z|x)+\int_{\underline{\varepsilon}}^{\bar{\varepsilon}}(\log\varepsilon-\mathbb{E}(\log\varepsilon))^3\,dA(\varepsilon)}{(Var(\log w|x))^{3/2}}.$$

D.3.5 Kurtosis

Let us denote with $K(\log w|x)$ the kurtosis of log-wages at actual experience x. Then,

$$K(\log w|x) = \frac{E\left[(\log w-\mathbb{E}(\log w|x))^4\,|x\right]}{[Var(\log w|x)]^2}$$
$$= \frac{E\left[(\log z-\mathbb{E}(\log z|x)+\log\varepsilon-\mathbb{E}(\log\varepsilon))^4\,|x\right]}{[Var(\log w|x)]^2}.$$

D.3.6 Minimum wage in the sample

Recall that, we fix the reservation rate in the model to equal the lowest observed wage in the data. Since we have no information on the firms' side (for example firm productivity), both worker and firm types are unobserved and we must impose additional assumptions to separately identify the supports of the two distributions. We choose to normalize the minimum worker ability $\log(\underline{\varepsilon})$ to zero, and this implies that the minimum wage implied by the model is

$$\log(w^{\min}) = \log(\underline{\varepsilon})+\log(z^R) = \log(z^R).$$