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

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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 gender 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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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 firms anticipate search costs and loss of 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 importance of turnover and human capital dynamics in driving the gender wage gap as men and women progress in their careers. We do so in a setting where firms form expectations regarding career interruptions 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. This is because meetings between workers and firms are sporadic and it takes time to form a new match. Thus, profit-maximizing employers might transfer expected costs of future turnover into lower wage offers to women. These costs of turnover might become especially high when skills accumulate fast in employment, potentially exacerbating gender gaps in high-learning environments. In addition, workers' search strategies and reservation wages are also impacted by their job prospects and skill accumulation rate in employment. 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.

We make three contributions to the literature. First, 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; Zhang, 2012; Bartolucci, 2013; Morchio and Moser, 2020). We extend these cross-sectional studies to a life-cycle analysis by including human capital accumulation 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). Moreover, 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. [1] We incorporate several factors affecting the career costs of having children in our equilibrium model, including the share of workers who retain their previous jobs after having a child, the typical durations of non-participation when workers return to previous jobs versus when they do not. This allows us to identify the dimensions of fertility-related career interruptions that contribute most to the gender wage gap.

Our model extends Burdett, Carrillo-Tudela, and Coles (2016) and 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 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 (a childcare period) 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, [2] 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.

Using the NLSY79, we first document gender-based labor market differences among high

[1] See, for example, Adda et al. (2017); Angelov et al. (2016); Kleven et al. (2019)

[2] In the US, federally mandated parental leave was introduced by the Family and Medical Leave Act (FMLA) in 1993. This act provides up to 12 weeks of job-protected but unpaid leave to workers in companies with over 50 employees.

school graduates and college graduates during the first 15 years of their careers. We focus on this period as this is when most of the life-cycle gap widening occurs (Goldin, 2014; Barth, Kerr, and Olivetti, 2017) and when workers tend to both experience intensive labor market turnover (Topel and Ward (1992)) and start families. We find that the hourly wages of high school and college women are 15 and 7 log points lower than those of men at the beginning of their careers, and these gaps expand to 28 and 33 log points 15 years after leaving school. Furthermore, 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. High school workers also have different transition patterns by gender. High school women have a much lower job-finding rate in non-employment than men (24% lower), and also a lower job-to-job transition rate (17% lower). Unlike the college group, the separation rates of high school men and women are comparable. For both college and high school groups, women spend more time in childcare periods 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. We recover job productivities from the structure of the model based on the wage gains upon job transitions as well as the shape of wage distributions 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 gender difference in workers' 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 career 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, the *job productivities channel* reflects productivity differences between jobs employing men and those employing women.

Our counterfactual analysis offers new insights into the structure of the gender wage gap at different points in life for different education groups. We find that gender differences in job productivities are a very important driver of the gap in the high school group, but do not matter much for the gap among college educated workers. As careers develop, the gender difference in human capital accumulation compounds over time and becomes a major factor of the college gender gaps, whereas it plays a minor role for less educated workers. Search capital differences — wage improvements due to on-the-job search — contribute more to the expansion of gender wage gap among college graduates than that among high school graduates. Finally, employers' equilibrium wage-setting accounts for around one-third of the gender wage gap for

both education groups over the first 15 years of their careers.

Our counterfactual exercises show that gender differences in turnover contribute substantially to the life-cycle gap, explaining 56% and 35% of the wage differential in the college and high school groups, respectively. Women's turnover patterns might disadvantage them in several dimensions, inducing wage discounts from employers on the one hand, and disrupting women's search capital and human capital accumulation on the other. The gender difference in separation rates stands out as the most important issue for the college group, contributing to a wage gap of 8 log points between college men and women, mostly driven by employers' wage-setting responses and disruptions to women's on-the-job search. For the high school group, women's low job arrival rates in both unemployment and employment are important factors, accounting for 3 and 2 log points in the wage gap. The former affects women's wages primarily through employers' responses and lower human capital accumulation, while the latter mostly hinders women's accumulation of search capital.

Moreover, 30% of high school women and 20% of college women do not return to their pre-birth employers after having children, and they tend to spend an extended period in non-employment after childbirth. Our counterfactual exercises show that such fertility interruptions not only decrease workers' human capital accumulation but also lower firms' wage offers, and suppress wage growth. In contrast, women who return to previous jobs after parental leave do not experience much wage deterioration as a result of fertility interruptions in the model counterfactual. This is because the duration of the childcare period is very short for those who retain their jobs, and thus it 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 must search for a new job after having a child would be especially beneficial for women's incomes.

Finally, we stress that human capital accumulation creates sizable interactions with the rest of the gender differences. In particular, increasing the skill 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. Additionally, firms value match stability more when employees' productivity grows faster, and they respond by shifting to a higher distribution[3] of wage rate offers. We find that these interactions in employers' wage-setting process can have major implications for the role of turnover differences in the wage gap. In our counterfactual exercise where firms do not consider the dynamics of human capital accumulation, the impor-

[3] Or first order stochastically dominant distribution

tance of turnover differences by gender would be underestimated by 75% in their contribution to the wage offer gap.

1.1 Related Literature

A recent empirical literature on the gender wage gap has focused on quantifying the relative importance of gender differences in within- and across-firm wage growth using matched employer-employee data. Barth, Kerr, and Olivetti (2017) and Goldin, Kerr, Olivetti, and Barth (2017) find that both channels are important in the U.S. 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 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 in our model).

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 endogenous firm responses explain a significant portion of the fertility-related gender wage gap, especially early in a 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 extend the idea of statistical discrimination in two important ways. First, differential behaviors in our model go beyond gender differences in the participation margin. Second, we include two aspects that arise in a non-competitive and frictional labor market— the strategic behavior of the firms that compete for workers, and the imperfect and differential mobility of men and women across jobs.

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). Previous literature has also studied the gender pay gap through the lens of equilibrium search models. Flabbi (2010) estimates the gender gap due to employers' taste-based discrimination; Bowlus (1997), Bowlus and Grogan (2009) and Bartolucci (2013) analyze wage gaps that arise as a result of turnover differences 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 of these turnover effects 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 gradu-*

ates, and those who have 16 to 20 years of schooling are *college graduates*.[4] 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.[5]

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).

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:

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

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.

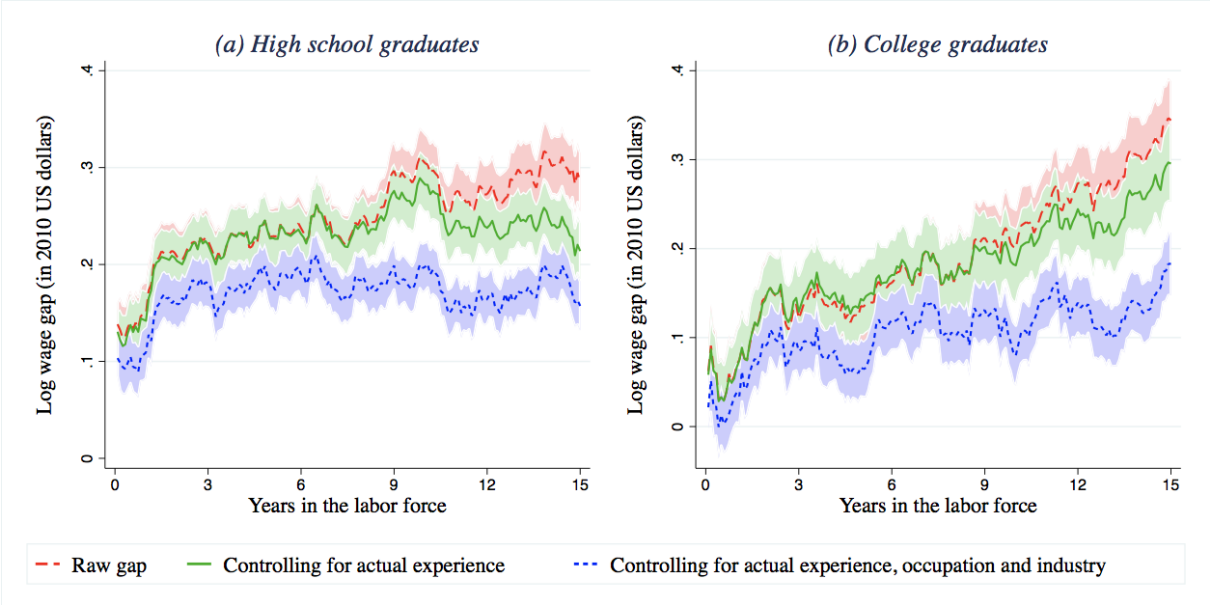
Figure 1 shows the log hourly wage gap between men and women by potential experience: *(i)* in the unadjusted specification in equation (1); *(ii)* adding a fourth order polynomial in actual experience to equation (1); and *(iii)* adding occupation and industry fixed effects and their interactions in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

[4] 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.

[5] 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.

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 (including only year FEs); *(ii)* adding actual experience controls; and *(iii)* adding occupation and industry controls in addition to actual experience. The shaded areas represent 95% confidence intervals.

respectively. This suggests that similarly qualified men and women receive unequal pay for doing similar jobs, potentially due to employers' 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 employers' expectations about workers' future behaviors. Therefore, these differences may impact employers' 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 employers' wage-setting policies in equilibrium.

Table 1 presents several aspects of gender differences related to labor market turnover and

fertility interruptions. In the first 15 years of their working lives, 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., 1.5 and 1.1 years less than their male counterparts, respectively). 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.

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
	(4.07)	(3.65)	(3.65)	(3.33)
Number of children	1.49	1.19	1.37	1.28
	(1.18)	(1.14)	(1.21)	(1.24)
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
	(2.55)	(0.96)	(4.42)	(0.16)
if start a new job (months)	16.99	4.49	14.81	3.65
	(17.17)	(5.56)	(18.01)	(3.91)
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

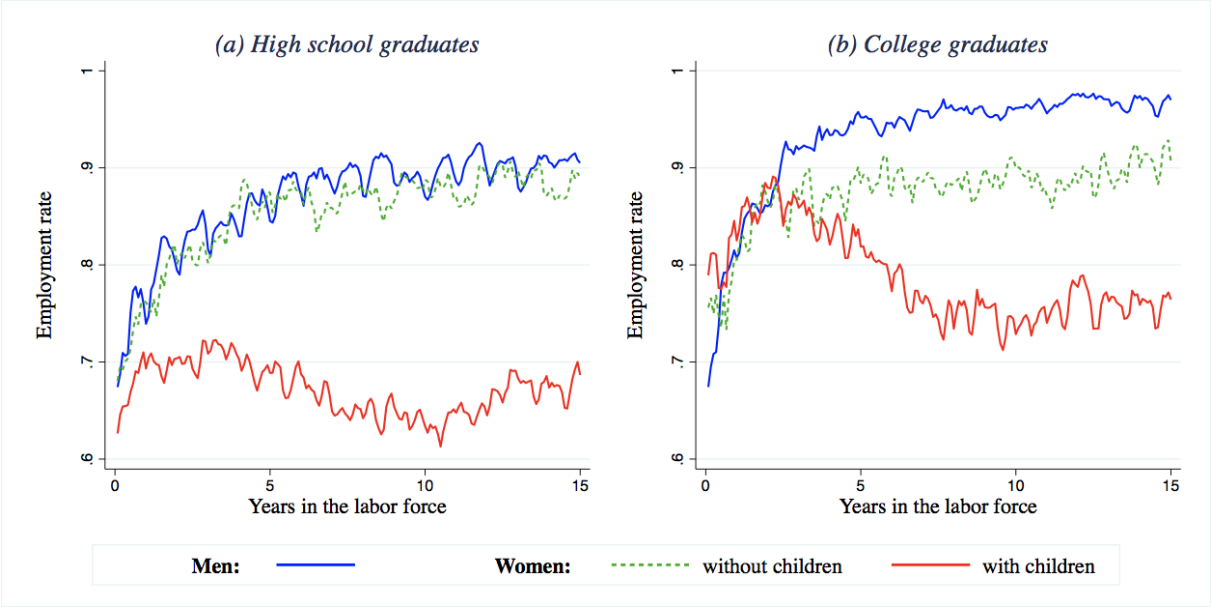
Notes: This table reports summary statistics of our NLSY79 sample over the first 15 years that workers spend in the labor market. Standard deviations are in parentheses.

In order to examine fertility-related career interruptions, we use the information in the NLSY79 on the timing of childbirth. We infer child-related non-employment from the workers' employment history by assuming that a worker is in a childcare period if she or he is non-employed in any of the 12 weeks before or the first 20 weeks after the child is born. If the worker returns to the pre-childbirth job, renewed employment marks the end of the childcare period. If the worker does not return to the pre-childbirth job, the childcare period ends with

the worker starting to search for a new job.[6] We do not observe these transitions from non-participation (in the childcare period) to participation (in unemployment where workers start job search), so in estimation we use the non-employment periods outside of fertility events to infer the lengths of child-related non-employment for such cases.

In our sample, women have slightly higher fertility rates than men. However, women stay out of the labor force after each childbirth for a longer period than men. According to our definitions, women spend about 2 months in a childcare period if they return to their previous jobs, whereas men spend only a week. Those who do not return to their pre-childbirth jobs spend a much longer time in non-employment: high school and college women stay home for 17 and 15 months respectively, and men in the same situation spend about 4 months in non-employment.

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.

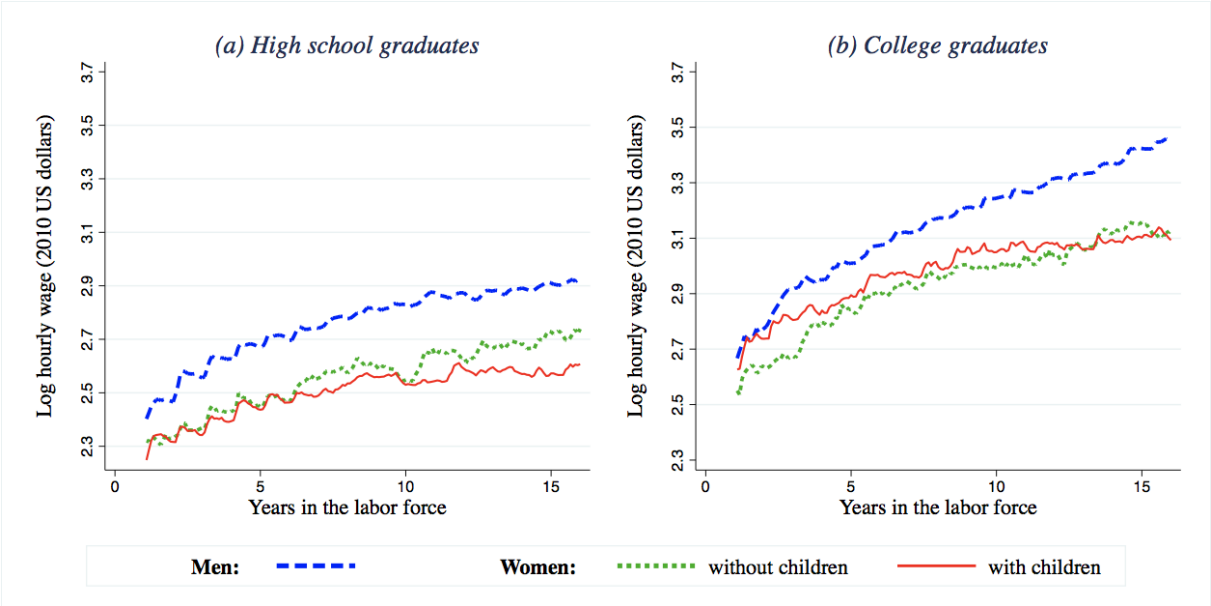
Although most of the childbirths in our sample happened before job protection was mandated by the Family and Medical Leave Act (FMLA) in 1993, a substantial share of women

[6]There might be several reasons why the workers do not return to previous employers. For example, the worker can be non-employed before childbirth, the worker's employer may not offer parental leave, or the worker may prefer to stay in childcare period for longer and give up the opportunity to return. We do not distinguish between these possible reasons and consider all periods where workers do not come back to their pre-childbirth jobs as the same type of childcare period.

(70% of high school women and 81% of college women) were able to go back to their old jobs after having children. These rates are much higher for men (90% and 95% for high school and college men, respectively), presumably because they usually go back to work immediately after childbirth. We incorporate these gender differences into our model, including the shares of workers returning to their old jobs, and durations of child-related non-employment.

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 towards women.

Figure 3: *Wage profiles of women with and without children*



Notes: This figure plots the average log wages in month after labor market entry. The blue dashed-line plots men's average monthly log wages, the green dotted-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.

Figure 3 provides suggestive evidence that such differential wage-setting 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, potentially because the former spend more time working and accumulate more human capital. A similar pattern 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.

In the next section, we lay out a model where rational and forward-looking employers are able to set wage offers differentially for men and women, taking into account expected labor market behavior of each group.

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 job 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 employer's problems in one of the four labor markets. All gender $g \in \{m, f\}$ and skill superscripts $s \in \{\text{Highschool, College}\}$ 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 employers 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 $\left[\underline{p}, \overline{p}\right]$.[7] Every employer 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 starts working at the job 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 employer posts to maximize steady-state expected profits.[8] The flow productivity of the match (y, p) is yp, so that the employer's flow profit from the match (y, p) is $(p - z)y$. Thus, each employer p chooses an offer z to maximize its aggregated expected steady state profits $\pi(p, z)$ from all the matches that will be formed.[9]

Let $F(z)$ denote the wage offer distribution, the fraction of the jobs that offer wage rates no greater than z. This offer distribution is determined in equilibrium through employers' optimal choice of z.[10]

Workers can receive job offers both while unemployed and while employed, according to 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 job may end for a number of reasons: first, a worker might be poached by another employer 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 childcare 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 childcare period is denoted by NJ and terminates at a different rate γ_3, upon which they enter

[7] 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.

[8] Since markets are segregated in the model, employers can set gender-specific wages. We could interpret this as employers 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, employers could feasibly claim that women are less productive and offer them lower wage rates.

[9] Frictions give monopsony power to employers, who 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., $w = \theta py$).

[10] 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 period of unemployment to look for new jobs. Those who are unemployed at childbirth will enter childcare periods 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.[11] 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 childcare period ends.[12]

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 $U(y)$:

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

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 an employer 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

[11] 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.

[12] While treating η as exogenous is a limitation of the model, it also reflects the policy environment of the time — before the FMLA was introduced, workers might have lacked information about whether the employer provides job protection, so they would assume that they could 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.

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 job 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

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

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 job offering wage rate z' if $V(y,z) < V(y,z')$. Since human capital is both general and transferable across jobs, 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

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

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 employers and taken up by workers in the labor market. If the worker has another child during the leave period, she loses the opportunity to go back to her previous employer. 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 childcare state of NJ type, with value $W^{NJ}(y)$ given by

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

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 availability of daycare, and so on.

As we show in Appendix C.1,[13] 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 $F(z)$.

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*

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

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.

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

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

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 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.

We make a number of simplifying assumptions that are necessary to keep the model tractable, including exogenous linear human capital accumulation technology, exogeneity of transition rates and childcare leave durations, and linearity of the flow utility in all states.[14] The goal of this paper is to quantify the effects of employers' wage-setting considerations. Therefore, we abstract from the intra-household decisions and do not take a stand on how they drive turnover and fertility-related career interruptions. We leave these important questions for future research.

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 employed workers, of measure m_E; *(ii)* unemployed workers, of measure m_U; *(iii)* those in childcare periods who have an opportunity to return to their old jobs afterwards, of measure m_{OJ}; and *(iv)* those in childcare periods who will have to search for new jobs, 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 $N(x)$, employment $H(x)$, OJ, and NJ states ($N^{OJ}(x)$ and $N^{NJ}(x)$, respectively) must also remain constant in steady-state equilibrium. 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 childcare periods with job retention. Since fertility and job retention are random events, every employed worker has the same probability of having a child and retaining a job at any point in time, regardless of her wage rate. In other words, $H^{OJ}(x,z) = H(x,z)$.

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

[14] As has been noted by Dey and Flinn (2008), linear utility implies that optimal decisions of individuals in a couple will be identical to the decisions of the same individuals when each one maximizes her own utility

3.3 Employers' Profits

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

We assume that all employers are active and thus they all offer wage rates $z \geq z^R$. An employer with productivity p chooses a wage rate z that maximizes its steady-state expected profit. When an employer 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 employer from this match is $(1-\theta)py = y(p-z)$, where $z = \theta p$. Since there is no discounting on the employer side , the steady-state expected profit is given by

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

where $y^{init}(z)\, y^{acc}(z)$ is the total expected human capital stock accumulated over the entire expected duration of a match. This expected human capital stock consists of two parts — the first part is the *initial* average human capital of new hires that the job 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 hold the job, which we denote by $y^{acc}(z)$.

Since employers 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

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

Since we do not limit the number of children per worker, employers must take into account that any worker joining its workforce might have children over the course of her job spell, each time potentially exiting to 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 employer 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 labor market exit ϕ, exogenous destruction shock 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 an additional fertility shock and before exiting the labor market — 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 employer's problem becomes

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

where $\widetilde{\varepsilon}$ denotes the expected productivity upon labor market entry.

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

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

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 so that more productive jobs post higher wage offers.

Proposition 2 represents part of the equilibrium that is complementary to Proposition 1. Equation 11 describes employers' 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 would decrease offers, because employers' 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, employers' 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 optimal offer $z = \xi(p)$ maximizes employers' 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 and the shapes 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 jobs 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. Following the literature (Hornstein, Krusell, and Violante, 2011), we assume a monthly discount factor $r = 0.0041$. The exit rate ϕ is fixed at 0.0033 so that workers have an average of 25 years of prime-age career. Since the model takes as exogenous the nonemployment duration after childbirth, it does not allow us to identify b^{out} separately from b. Therefore, we set $b^{out} = b$. There are thus fifteen parameters to estimate for each gender and education group — ρ, $\underline{p}$, $\overline{p}$, κ_1, κ_2, α_1, α_2, b, γ_1, γ_2, γ_3, η, δ, λ_e, and λ_u.

Out of the above fifteen parameters, the seven Poisson rates have direct data counterparts and are thus exactly identified. In the spirit of Bowlus and Eckstein (2002), we derive closed-form expressions for fertility and turnover moments in the data as functions of the Poisson rates γ_1, γ_2, γ_3, η, δ, λ_e, and λ_u, independent of the other eight model parameters. The fertility rate γ_1 corresponds to the average number of children born during our sample period. The parental leave exit rate in OJ, denoted by γ_2, is identified by the average duration of career interruption for workers who had a child in employment and returned to their previous job. The parental leave exit rate in NJ, γ_3, is identified by the average duration of child-related leave of workers who had a child in non-employment, net of regular non-employment duration. The OJ return rate η is identified by the fraction of women who return to their previous employers out of all women who have a child when employed. The offer arrival rate in unemployment λ_u and the exogenous separation rate δ are identified by the job-finding and separation rates outside of fertility events. 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, and skewness 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 tar-

geted 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 by different firms. Therefore, targeting both such wage changes and the overall life-cycle wage growth pins down the human capital accumulation rate ρ, which captures 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 job 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 employer-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).

Finally, 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 the inverse of the diagonal variance-covariance matrix of the data

moments [15] 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 childcare periods 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%
		(0.001)	(0.001)		(0.001)	(0.001)	
Offer arrival rate							
in U	λ_u	0.185	0.252	-26.6%	0.222	0.258	-14.1%
		(0.005)	(0.009)		(0.010)	(0.016)	
in E	λ_e	0.092	0.118	-21.9%	0.087	0.087	-0.7%
		(0.002)	(0.002)		(0.002)	(0.002)	
Fertility rate ($\times 10^{-2}$)	γ_1	0.827	0.663	24.7%	0.762	0.709	7.3%
		(0.017)	(0.016)		(0.025)	(0.027)	
Childcare exit rate							
in OJ	γ_2	0.496	3.162	-84.3%	0.532	6.892	-92.3%
		(0.027)	(0.352)		(0.062)	(0.375)	
in NJ	γ_3	0.022	0.119	-81.8%	0.013	0.305	-95.8%
		(0.002)	(0.141)		(0.002)	(0.378)	
OJ return rate	η	0.711	0.900	-21.1%	0.822	0.956	-13.9%
		(0.016)	(0.009)		(0.016)	(0.008)	

Notes: This table reports the point estimates of our just-identified parameters and their standard errors in parentheses. U denotes non-employment; E denotes employment; OJ is the childcare state where workers have an option to return to old employers; NJ denotes the childcare state where workers search for new jobs. The percentages next to the estimates show the gender differences as a percentage of men's parameter values.

Table 3 shows the estimates of jointly estimated GMM parameters and their standard errors.

[15] In addition, we enhance the relative weight of our main two moments - wage levels and wage changes upon job-to-job transitions

All parameters are precisely estimated. We provide the details of the GMM procedure and the computation of standard errors in Section D.2.

Table 3: *Jointly estimated parameters*

		High school graduates		College graduates	
		Women	*Men*	*Women*	*Men*
ρ		2.614×10^{-3}	2.647×10^{-3}	2.324×10^{-3}	3.196×10^{-3}
		(0.000)	(0.000)	(0.000)	(0.000)
$\Gamma(p)$	$\underline{p}$	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)
$A(\varepsilon)$	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)
b		7.398	9.855	5.888	8.258
		(0.087)	(0.166)	(0.177)	(0.135)

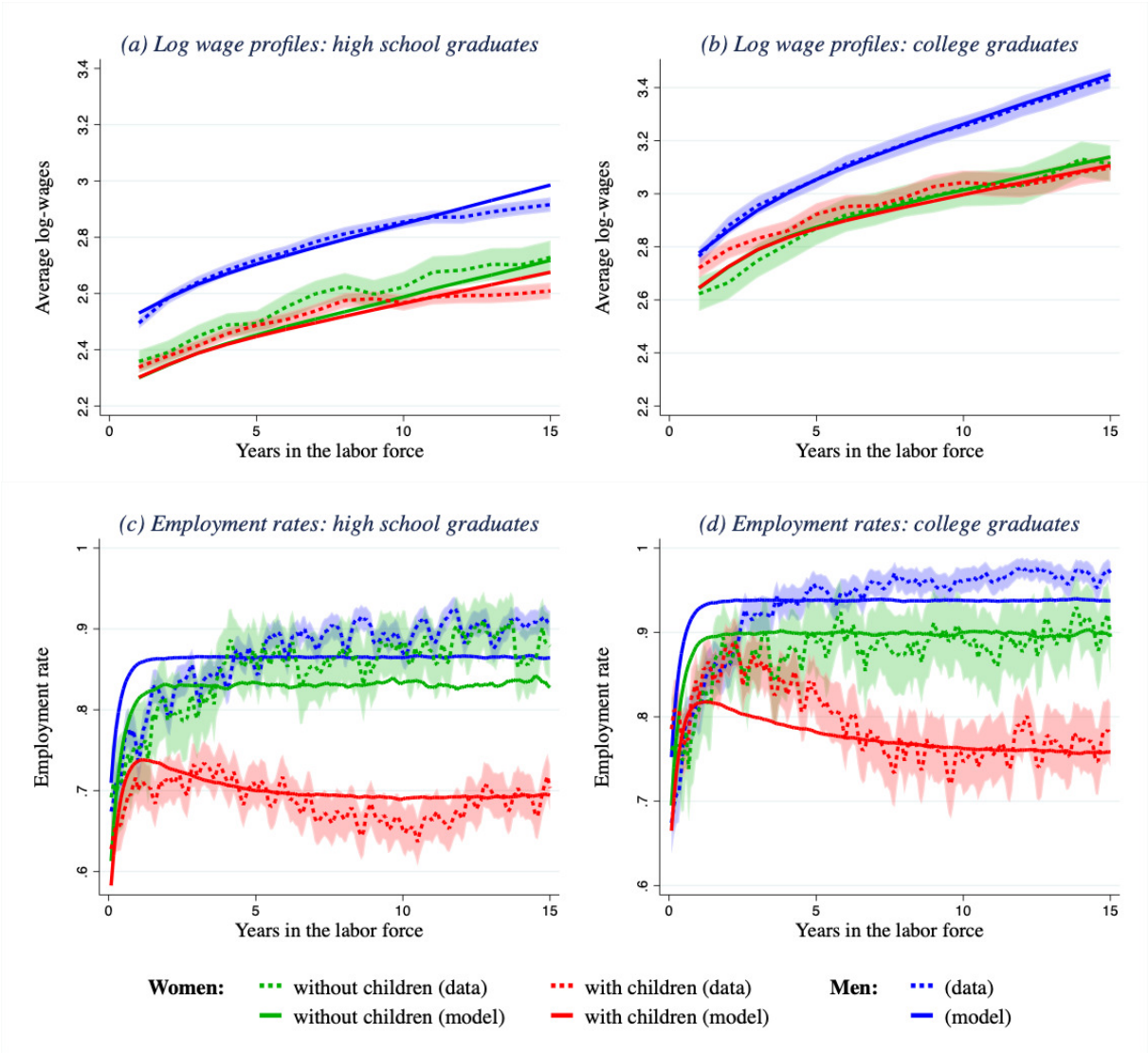
Notes: This table reports the point estimates of the jointly estimated parameters via GMM and standard errors in parentheses. The parameters $\underline{p}$, $\overline{p}$, κ_1 and κ_2 govern the firms' productivity distribution, $\Gamma(p)$, and α_1, α_2 determine $A(\varepsilon)$. Standard errors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

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 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.

The support of the job productivity distribution for men is shifted to the right compared to

that for women for college graduates, but not for high school graduates. 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

Figure 4: *Model fit of untargeted moments*



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 corresponding data moments. The shaded areas correspond to a point-wise 95% confidence interval.

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 levels 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 nor employment rates by potential experience, Figure 4 shows that our parameter estimates fit these untargeted moments very well for men and for women with and without children. 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. Likewise, employment rate profiles describe the evolution of employment stocks that follow from workers flows generated by our transition parameters. 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 prime ages of workers' careers. 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.[16]

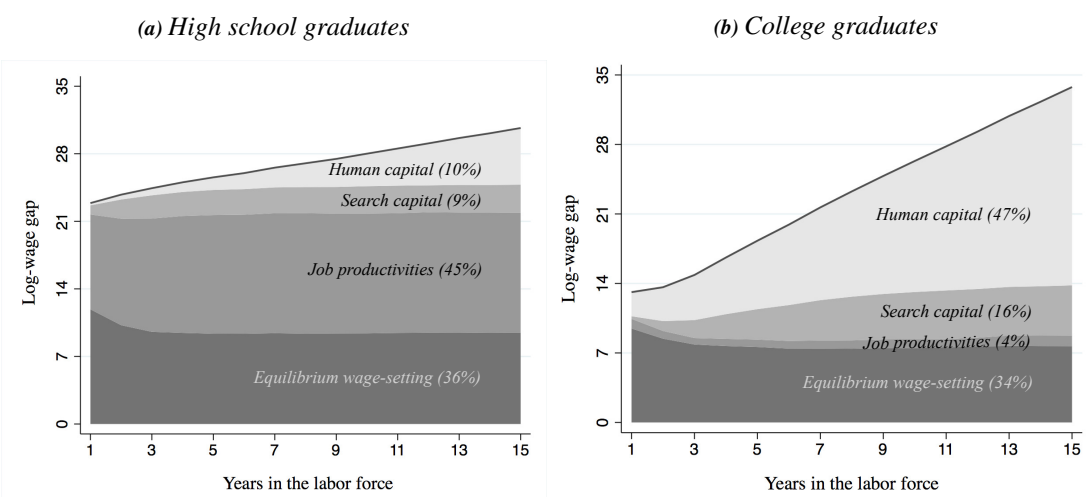
Using the above notation, we denote the average counterfactual wage rate at a given point in life by $\overline{\log(z)}\,|_{\Lambda,F(\Omega,\Theta)}$. Note that this average wage rate $\overline{\log(z)}$ is not only conditioned on the endogenous offer distribution $F(\Omega,\Theta)$, but also the speed with which workers climb the job ladder which is governed by Λ. For example, $\overline{\log(z)}\,|_{\Lambda^m,F(\Omega^f,\Theta^m)}$ 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

[16] 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).

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

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. [17]

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



Notes: The figure shows the total log-wage gap (with a black solid line) and its four components (in the gray areas) as shown in equation (13). In parentheses we show the percentage contribution of each channel averaged over the 15-year period.

[17] 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 illustrates the relative importance of these four components over potential experience. The solid black line represents the total gender wage gap, and the gray areas represent the four additive components outlined in equation (13).

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 same part of 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.[18]

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 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 *life-cycle expansion* of the gender gap, it is worth noting that the life-cycle dynamics 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 gender 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 observed expansion in the gender wage gap is driven by the human capital and search capital channels, which gain weight in explaining gender wage gap as the career progresses. The expansion of the gender gap for college graduates is almost entirely driven by the pronounced divergence of human capital

[18]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.

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.[19] 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 employers

Our model sheds light on the mechanisms behind employers' wage-setting process. Employers choose profit-maximizing wage rates that take into account expected 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.

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.

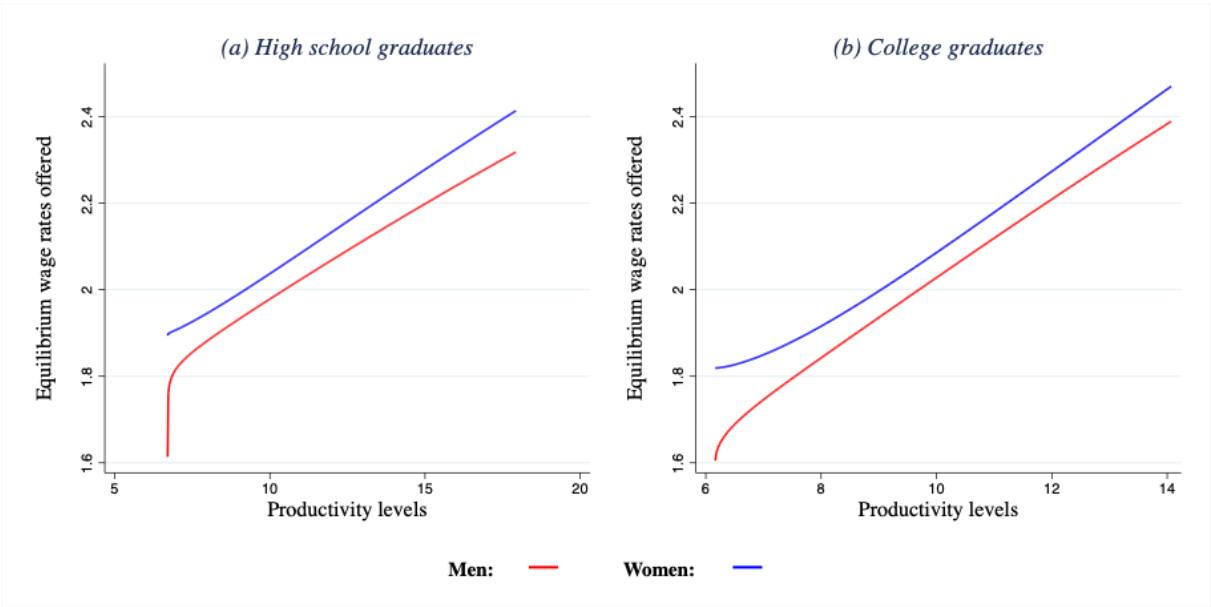
On average, women would get wage offers that are 13 and 10 log points lower than men in the high school and college groups, respectively. There is also considerable variation in the size of these gender gaps across the job productivity distribution. In both groups, the wage discounts towards women are much more pronounced in low-productivity jobs than in high-

[19] 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.

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 earned 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 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

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



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

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

		High school graduates		**College graduates**	
		Parameter change (%)	$\log(z)$ *change*	*Parameter change (%)*	$\log(z)$ *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

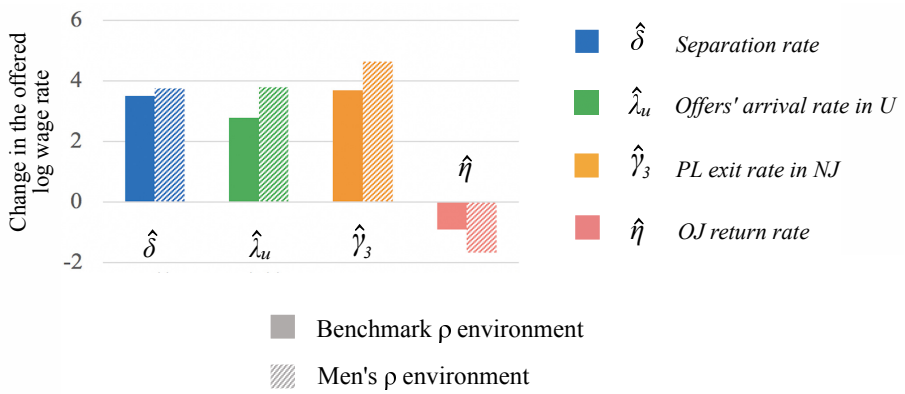
Notes: The table shows how women's log wage rates change upon equalizing each parameter to the level of men. A positive (negative) number in the *parameter change* column indicates the percentage increase (decrease) in women's parameter when it takes on men's value. The $\log(z)$ *change* columns show the changes in wage rates $\log(z)$ offered to women.

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 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 returning from 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 childcare periods, 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

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



Notes: The figure shows the increase (positive bars) or decrease (negative bar) in the offered wage rates for women when the parameter were to take men's value. The benchmark human capital accumulation environment keeps ρ at its estimated level for women, while the high learning environment takes the ρ value of men's.

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 has an opposite effect — it widens the gap in average offered wage rates 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. 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 gap in wage offers 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.

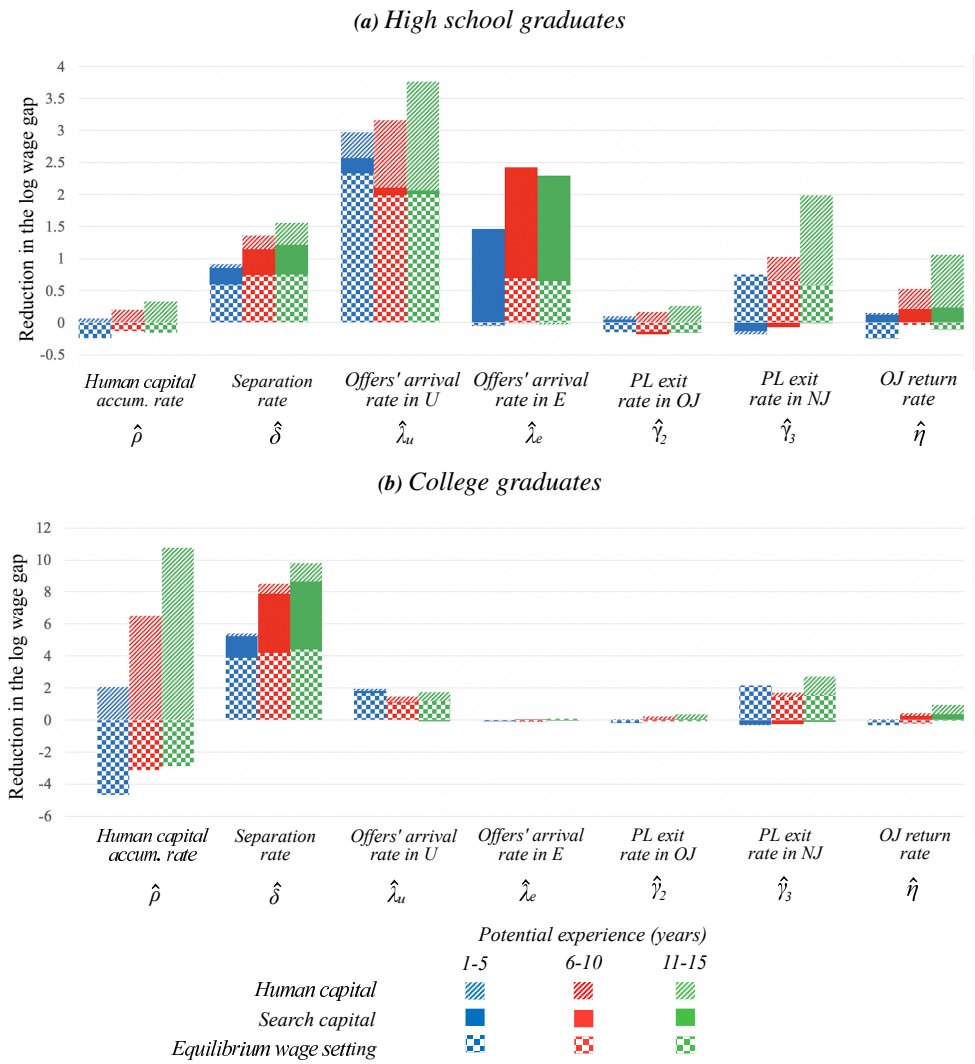
In the following section, we explore how these differences in equilibrium wage offers — wage ladders — combine with the differences in the speed of climbing the ladder and in human capital accumulation and shape the gender gap over the life-cycle.

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 shows the extent to which each parameter contributes to the gender wage gap at different points of the life-cycle if women were to have men's parameters. Table 5 shows the corresponding numbers averaged over the entire horizon. 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

Figure 8: *The effect of each parameter on the gender wage gap at different points of the life-cycle*



Notes: The positive (negative) bars indicate an increase (decrease) in women's wages at different points of the life-cycle, when women's parameter takes on men's value. The striped portion of each bar shows the increase (decrease) in women's wages attributed to the human capital channel, the solid portion represents the search capital channel, and the checkered portion reflects firms' wage-setting channel.

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 low 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 in years 1-15 (as seen in Table 5). After having children, high school women spend a much longer time in non-employment

Table 5: *Total effect of each parameter on the gender wage gap over the first 15 years of potential experience*

		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 average increase in women's wages over the entire life-cycle (in log points) when each parameter takes on men's value. The bottom row shows the average log wage gap at estimated values of the parameters.

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 (accounting 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 expanding gender wage gap. The first one is the higher separation rate of women δ, accounting for 34% of the gap (see Table 5). 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

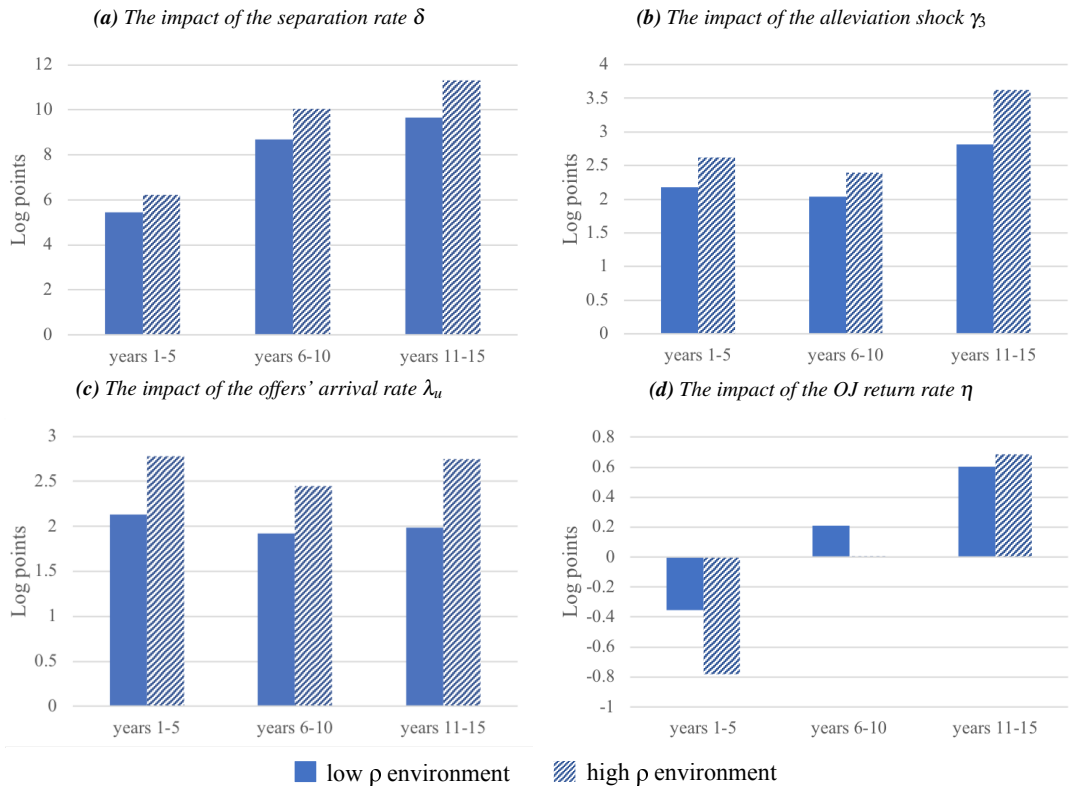
human capital growth, they would be willing to accept lower starting wages and thus would face lower equilibrium offers; however, over the years they would enjoy a dramatic increase in human capital that more than compensates for the decrease in their initial wage rates, as shown by striped bars in Figure 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 very early career. It is crucial for policies to improve women's labor force attachment and mobility (i.e., by reducing their quit rates and increasing job-finding rates in all employment states), because these policies will make employers change their expectations about men and women and offer similar wage 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 on the gender wage gap 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 years, 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

Figure 9: *The life-cycle effects of turnover parameters in high- and low-ρ environments*



Notes: The positive (negative) bars show the increase (decrease) in women's wages at different points of the life-cycle when the parameter takes men's value. The solid bars show the wage changes in the benchmark human capital accumulation environment where ρ takes women's value, while the striped bars show corresponding changes in a high learning environment where ρ takes the value of men's.

parental leave), the effects are reversed in later years as more women are able to accumulate skills in a more stable employment after each 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 cannot 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.

6 Conclusion

This paper studies the life-cycle gender wage gap through the lens of an equilibrium search model. Our analysis distinguishes between the human capital and frictional components of the gender wage gap, while accounting for the equilibrium firm decisions in response 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, employer-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 career. 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. 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.

Two caveats are worth stressing with respect to the above results. First, the model focuses entirely on utility from wages, and is silent on the potential gains in value that happen when workers stay at home to take care of their children, both in terms of parents' own utility and in terms of any short- or long-term benefits that accrue to children. Therefore, policies that we identify as efficient for increasing women's wages will not necessarily improve women's or children's welfare. Addressing these issues would be challenging in our framework but is an important avenue of future research. A second, related point, is that we take as given the gender differences in labor market behaviors, and remain agnostic about their underlying causes. Therefore, though the model uses counterfactual policy exercises that change women's behavior to identify the margins driving the wage gap, the results we provide serve an upper bound of the potential impact of such policies in practice. This is because behavior differences between men and women can be driven by family-related preferences on the one hand, and labor market constraints on the other hand (including frictions, employer discrimination, early childcare availability), so addressing only the constraints may not be sufficient in reducing the gender wage gap.

Our analysis opens up a number of potentially important margins to take account of in future research on gender inequality. 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.

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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.[20] The data in Waldfogel (1999) show that no more than 40% of employees in medium to large firms[21] (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.

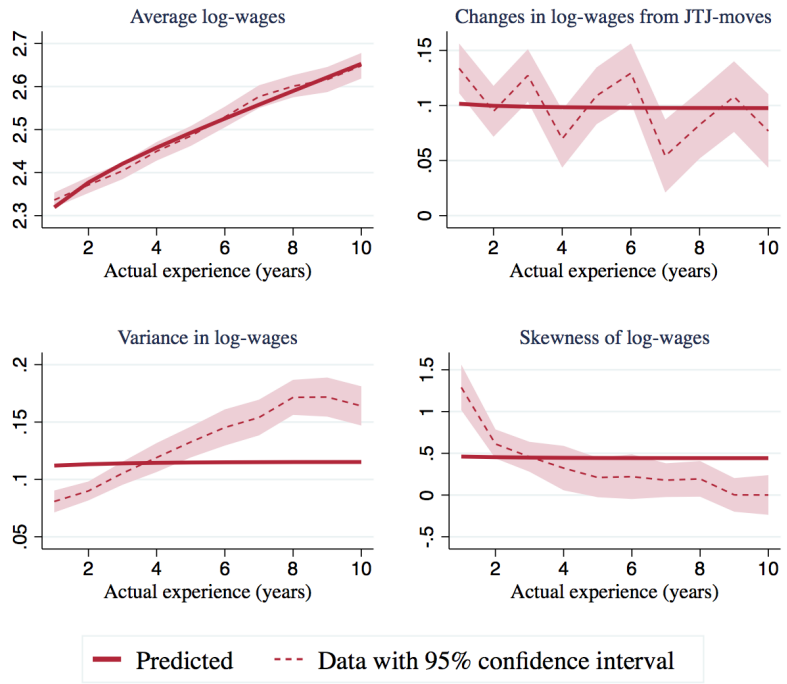
[20] Only six states (California, Connecticut, Massachusetts, Minnesota, Rhode Island, and Washington) required at least some private sector employers to offer maternity leave coverage prior to 1988. See more details about US maternity leave policies in Berger and Waldfogel (2004).

[21] 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

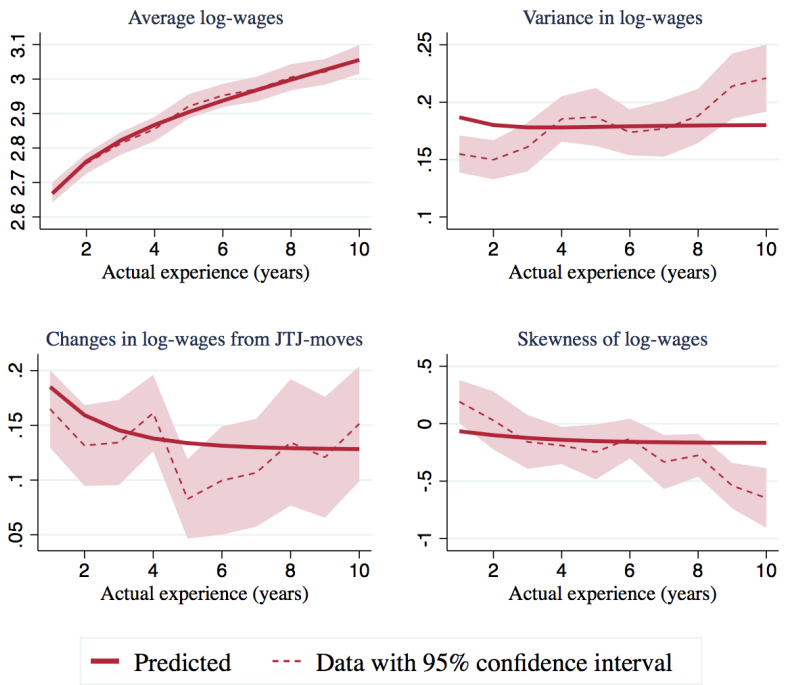
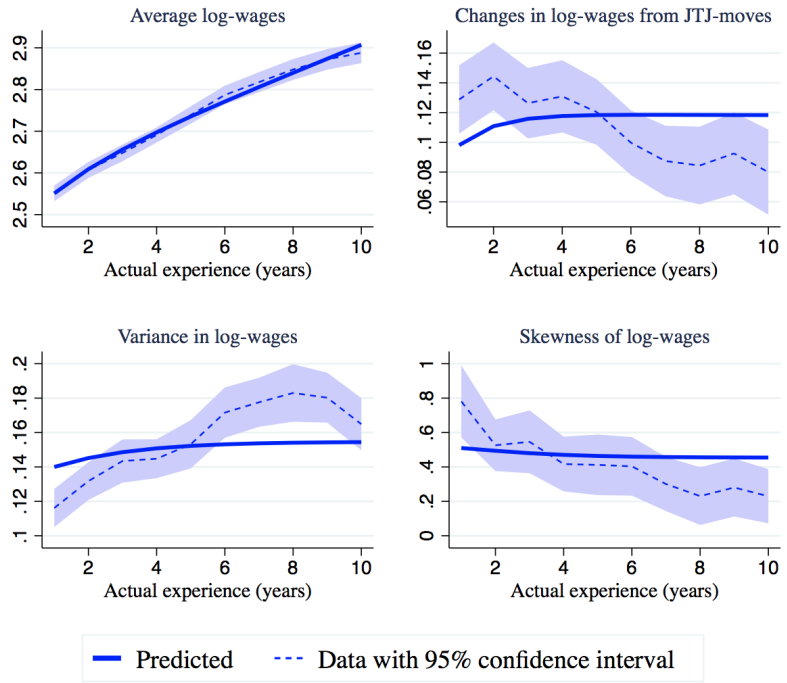
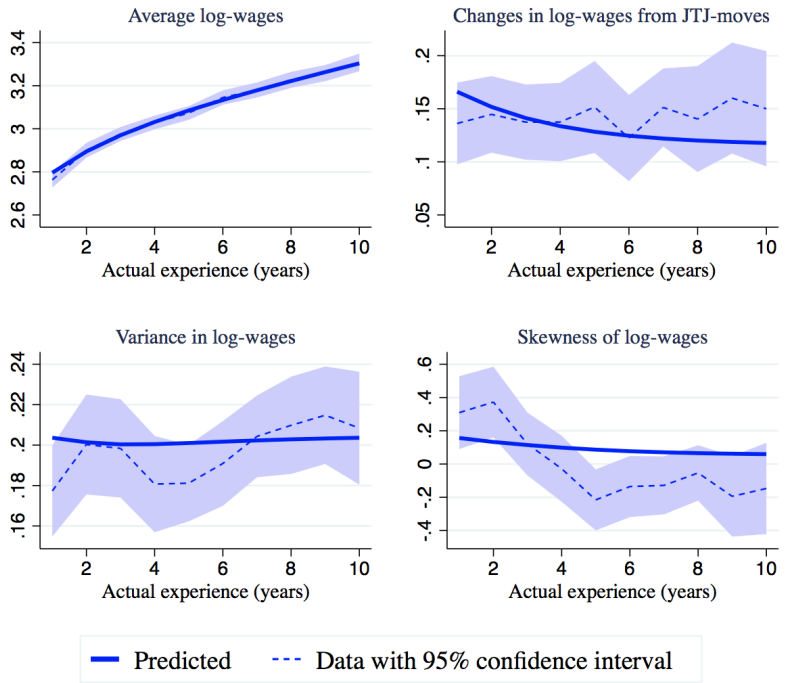


Figure B.2: *Fit of the targeted moments in GMM estimation for men*

(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

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

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,

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

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

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

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

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

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

obtained by evaluating (16) and (18) at $\overline{z}$ 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

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

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:

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

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 $z^R=\overline{z}$, the left-hand side is positive, while the right-hand-side is 0. Therefore, there exists a unique $z^R<\overline{z}$ 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

$$\pi(z,p) = y^{init}(z)\,y^{acc}(z)(p-z) = \frac{\zeta_4}{M(z)^2}(p-z).$$

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

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

It remains to show that Equation 25 indeed satisfies the first-order condition of employers' profit-maximization problem and that no other offer can be profit-maximizing.

We follow Burdett, Carrillo-Tudela, and Coles (2016) to show the above points.

First, note that the profits can be expressed as:

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

where $\ell(z) = \frac{\zeta_4}{(M(z))^2}$. Thus, the following first order condition must hold for any profit-maximizing offer z,

$$\ell'(z)(p - z) - \ell(z) = 0.$$

Using the expression for $\ell(z)$ from above, $\ell'(z) = (-2\zeta_4 M'(z))/(M(z))^3$ and hence,

$$\ell'(z)(p-z) - \ell(z) = \frac{-2\zeta_4 M'(z)(p-z)}{(M(z))^3} - \frac{\zeta_4}{(M(z))^2} = 0$$

so that

$$\frac{-2M'(z)(p-z)}{M(z)} = 1. \tag{27}$$

Note also that differentiating equation (25) with respect to p yields exactly the same expression as in equation (27) above.

Next, we show that for any job p offering a z that is an optimal policy for some other job $\hat{p}$ can not be profit maximizing. Let $\pi(\xi(\hat{p}); p)$ denote profits of employer p when offering a wage rate $z = \xi(\hat{p})$. Let $\Delta(\hat{p}) = \hat{p} - p > 0$. For $\hat{p} \in (p, \overline{p})$ the second order condition for profit maximization requires that offering such a z should not increase profits. Indeed:

$$\begin{aligned}
\left[\frac{d\pi(\xi(x);p)}{dx}\right]_{x=\hat{p}} &= \left[\frac{d\ell(\xi(x))}{d\xi}\xi'(x)(p-\xi(x)) - \xi'(x)\ell(\xi(x))\right]_{x=\hat{p}} \\
&= \xi'(x)\left[\frac{d\ell(\xi(x))}{d\xi}(x-\Delta(x)-\xi(x)) - \ell(\xi(x))\right]_{x=\hat{p}} \\
&= \xi'(x)\left[\underbrace{(x-\xi(x))\frac{d\ell(\xi(x))}{d\xi} - \ell(\xi(x))}_{=0} - \Delta(x)\frac{dl(\xi(x)}{d\xi}\right]_{x=\hat{p}} \leq 0,
\end{aligned}$$

where the first term inside the square brackets in the last line of the equalities above, is 0 as the first order condition is satisfied. Similarly, one can show that for a job p offering a wage rate that is optimal for a $\hat{p} \in [\underline{p}, p)$ (in which case $\Delta(\hat{p}) = \hat{p} - p < 0$) results in lower profits as well:

$$\left[\frac{d\pi(\xi(x);p)}{dx}\right]_{x=\hat{p}} = \xi'(x) \cdot \left[-\Delta(x)\frac{d\ell(\xi(x))}{d\xi}\right]_{x=\hat{p}} \geq 0.$$

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:

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

with $\zeta_5=(\lambda_u-\lambda_e)\left(r+\phi+\gamma_1+\gamma_3\right)-\frac{\rho(r+\phi+\gamma_3)\lambda_u}{r+\phi}+\frac{(\gamma_3-\gamma_2)\eta\lambda_u\gamma_1}{r+\phi+\gamma_1+\gamma_2}$ 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,

$$\int_{z^R}^{\bar{z}}\frac{(1-F(z))}{\left(q(z)+r-\rho-\frac{\eta\cdot\gamma_1\cdot\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}dz=\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\xi'(x)dx.^{22} \tag{28}$$

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

$$\xi'(p)=\left(\frac{\left(\underline{p}-z^R\right)}{M(\xi(\underline{p}))^2}+\int_{\underline{p}}^{p}\frac{1}{M(\xi(x))^2}dx\right)\Psi(p). \tag{29}$$

Summing up using equation (22),

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

Then, using equation (28),

$$\frac{(\gamma_3-\gamma_2)\gamma_1\eta}{r+\phi+\gamma_1+\gamma_2}\left(b^{out}-b\right)=\left(b-z^R\right)\left(r+\phi+\gamma_1+\gamma_3\right)-\rho\frac{b\left(r+\phi+\gamma_3\right)+\gamma_1 b^{out}}{r+\phi}$$

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

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

□

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 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

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

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},

$$D_{EtoU} = \frac{\delta}{\phi + \delta + \gamma_1} \left(1 - e^{-(\phi+\delta+\gamma_1)}\right). \tag{31}$$

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

$$\mathbb{E}(JP \text{ duration}) = \frac{1}{\phi + \gamma_1 + \gamma_2}. \tag{32}$$

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,

$$\mathbb{P}(\text{Come back}) = \frac{\eta\gamma_2}{\phi + \gamma_1 + \gamma_2}. \tag{33}$$

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

$$D_{EtoE}|x = \int_{\underline{z}}^{\overline{z}} D_{EtoE}(z)dH(z|x), \tag{34}$$

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 $F(z)$.[23] 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

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

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

[23] 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 $\overline{z}$ and at $\underline{z}$.

To algebraically show that (34) 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

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

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

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

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

which does not depend on F. Thus,

$$
\text{Job Duration} \quad = \quad K \left[\begin{array}{l} \left[\frac{\phi+\gamma_1+\gamma_2}{\eta\,\gamma_1\,\gamma_2}\right]^2 \frac{1}{\lambda_e} \ln\left(\frac{\phi+\delta+\gamma_1+\lambda_e}{\phi+\delta+\gamma_1} \frac{\phi+\delta+\gamma_1-\frac{\eta\,\gamma_1\,\gamma_2}{\phi+\gamma_1+\gamma_2}}{\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\,\gamma_1\,\gamma_2}{\phi+\gamma_1+\gamma_2}} \right) \\ + \frac{\phi+\gamma_1+\gamma_2}{\eta\,\gamma_1\,\gamma_2} \frac{1}{\left(\phi+\delta+\gamma_1-\frac{\eta\,\gamma_1\,\gamma_2}{\phi+\gamma_1+\gamma_2}\right)\left(\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\,\gamma_1\,\gamma_2}{\phi+\gamma_1+\gamma_2}\right)} \end{array} \right] \tag{35}
$$

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,

$$\frac{dH(z|x)}{dz} = \frac{f(z)}{e^{-(q(\bar{z})-\omega)x} + \frac{n_2\left(R_1 e^{-R_1 x} - (q(\bar{z})-\omega)e^{-(q(\bar{z})-\omega)x}\right)}{q(\bar{z})-\omega-R_1}} \times \left[\begin{array}{c} e^{-(q(z)-\omega)x} + \frac{n_2 R_1 e^{-R_1 x}}{q(z)-\omega-R_1} - \frac{n_2 e^{-(q(z)-\omega)x}}{1-\frac{R_1}{(q(z)-\omega)}} \\ +\lambda_e F(z) \left(\begin{array}{c} e^{-(q(z)-\omega)x} x + \frac{n_2 R_1 e^{-R_1 x}}{(q(z)-\omega-R_1)^2} - \\ -\frac{n_2 e^{-(q(z)-\omega)x}(x(q(z)-\omega)(q(z)-\omega-R_1)+R_1)}{[q(z)-\omega-R_1]^2} \end{array} \right) \end{array} \right], \tag{36}$$

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 $f(z) = \frac{dF(z)}{dz} = \left.\frac{\Gamma'(p)}{\xi'(p)}\right|_{z=\xi(p)}$. Note that from the equilibrium solution we have an analytical expression for $\xi'(p)$

(see equation (29)). 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

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

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,

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

so that

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

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

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

and hence

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

D.3.4 Skewness

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

$$S(\log w|x) = \mathbb{E}\left[\left(\frac{\log w - \mathbb{E}(\log w|x)}{(Var(\log w|x))^{0.5}} \right)^3 |x \right]$$
$$= \frac{\mathbb{E}\left([\log \varepsilon + \rho x + \log z - (\rho x + \mathbb{E}(\log z|x) + \mathbb{E}(\log \varepsilon))]^3 \Big| x \right)}{(Var(\log w|x))^{3/2}}$$
$$= \frac{\int_{z^R}^{\bar{z}} \left(\log z - \log z^R - \int_{z^R}^{\bar{z}} \frac{1-H(z|x)}{z} dz \right)^3 dH(z|x) + \int_{\underline{\varepsilon}}^{\bar{\varepsilon}} (\log \varepsilon - \mathbb{E}(\log \varepsilon))^3 dA(\varepsilon)}{(Var(\log w|x))^{3/2}}.$$

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

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