Human Capital Accumulation, Equilibrium Wage-Setting, and Gender Pay Gap Dynamics

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Abstract

We study how turnover and human capital accumulation shape the gender pay gap dynamics early in the life-cycle 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 gender wage 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. Importantly, neglecting the interaction between turnover and human capital dynamics leads to a substantial downward bias in the estimated contribution of turnover to the wage gap.

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

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1 Introduction

The gender pay gap widens substantially over the course of workers' careers, especially among highly educated workers (Barth, Kerr, and Olivetti, 2021). An extensive literature emphasizes gender differences in human capital accumulation as an important driver of this divergence in career outcomes, 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 Blau and Kahn (2017) and Blau, Kahn, Boboshko, and Comey (2024) for a review). In a frictional labor market, part of this "unexplained" gap could reflect rational and forward-looking employers discounting the wages of high-turnover groups in anticipation of search costs and output losses. Understanding employers' wage-setting decisions is therefore critical to studying both the cross-sectional and dynamic components of the gender wage gap, and to designing policies that effectively target its underlying sources.

In this paper, we study how turnover and human capital dynamics contribute to the gender wage gap as men and women progress in their careers. We focus on a setting in which firms anticipate women's career interruptions (related to family responsibilities) and incorporate these expectations into wage offers. In the presence of search frictions, where meetings between workers and firms are infrequent and hiring is costly, women's weaker attachment and shorter match durations can impose substantial costs on employers. As a result, profit-maximizing firms may translate the expected costs of future turnover into wage markdowns for women.

The costs of turnover are likely to be more pronounced in environments where skills accumulate rapidly on the job, potentially exacerbating gender gaps in high-skill sectors. A key goal of the paper is to examine how firms' wage-setting policies vary across skill environments, with distinct implications for workers in different education groups. To disentangle the roles of human capital, firms' decisions and their interactions in the life-cycle gender wage gap, we develop an equilibrium search model of wage dynamics. We estimate the model separately for high school and college graduates using data from the 1979 National Longitudinal Survey of Youth (NLSY79), and quantify policy counterfactuals in different human capital environments.

Using the NLSY79, we first document gender gaps during the first fifteen years of men's and women's careers.[1] We find that the hourly wages of high school and college-educated women

[1] We focus on this period because it is when most of the life-cycle gap widening occurs (Goldin, 2014; Barth,

are 15 and 7 log points lower, respectively, than those of men at labor market entry. These gaps widen over time, reaching 28 and 33 log points fifteen years after leaving school. Labor market mobility also differs substantially by gender within education groups. College-educated women are 59% more likely than college-educated men to transition into non-employment. Among high school graduates, women have 24% lower job-finding rates from non-employment and 17% lower job-to-job transition rates compared to men. Moreover, both college and high school women spend more time in childcare leave than their male counterparts.

We also provide suggestive evidence that firms may set differential wages by gender in anticipation of women's fertility decisions.[2] We document that although childless women exhibit labor force attachment patterns closer to men's, their initial wages align with those of mothers rather than men. This pattern suggests that employers cannot perfectly predict individual fertility outcomes and instead set wages based on the average expected behavior of the group. Over time, however, childless women's hourly wages surpass those of mothers, potentially reflecting greater human capital accumulation through continued labor market participation. Our model captures both the initial wage gaps (between mothers, non-mothers, and men) and their evolution, formalizing how employer expectations and human capital dynamics jointly shape career trajectories.

The model features equilibrium wage-posting by employers, human capital accumulation through learning by doing, and on-the-job search. We allow skill accumulation rates, job arrival rates, and separation rates to vary by gender and across education groups. Following the birth of a child, both men and women enter a period of non-employment (childcare leave) in which they do not search for jobs, contribute to firm output, or accumulate human capital. To reflect the institutional setting in the U.S. during our data period, we assume parental leave is unpaid, and only a subset of workers retain job protection after childbirth.[3] We allow for taste-based discrimination as a residual component.

We estimate the model on NLSY79 data using the generalized method of moments. Job productivity distributions are inferred from the model structure, leveraging observed wage gains upon job transitions and the shape of wage distributions at different ages. For each education

Kerr, and Olivetti, 2021), and when workers tend to both experience intensive labor market turnover (Topel and Ward, 1992) and start families.

[2]Gallen (2024) and Bronson and Thoursie (2021) also find that employers systematically discount wages for women in prime childbearing years. They show that these wage discounts persist even after controlling for productivity and job characteristics, consistent with anticipatory statistical discrimination.

[3]Federally mandated parental leave was introduced in the U.S. by the Family and Medical Leave Act (FMLA) in 1993, which provides up to 12 weeks of unpaid, job-protected leave for employees at firms with over 50 workers. Firms with fewer than 50 employees (about 90% of U.S. firms according to Choi and Spletzer (2012) and Henly and Sánchez (2009)) are exempt from offering leave or job protection.

group, we conduct counterfactual exercises to decompose the gender wage gap into four additive channels based on the estimated parameters. First, the *human capital channel* captures the gender difference in workers' productivity growth during employment through learning by doing.[4] Second, the *search capital channel* reflects differences in the speed at which men and women move up the job ladder due to their turnover patterns, holding human capital and wage offers fixed. Third, the *equilibrium wage-setting channel* measures differences in wage rates offered to men and women in the same job for each unit of human capital. Fourth, the *job productivities channel* captures differences in the productivity of the jobs held by men versus women.

Our counterfactual analyses reveal striking differences in the sources of the gender wage gap between high school and college graduates over the first fifteen years of their careers. A key finding is that the human capital channel dominates for college-educated workers: estimated skill accumulation rates are 37.5% higher for college men than women, while the gender gap in learning rates is negligible among high school graduates (1.26%). Over time, these disparities compound, and the human capital channel ends up explaining 47% of the total gender gap for college workers, compared to just 10% for high school graduates. In contrast, the job productivities channel emerges as a more important driver of the wage gap among high school workers, but contributes little to the gap among college-educated workers.

The search capital channel accounts for 16% of the college wage gap and 9% of the high school wage gap across genders. Among college graduates, the gender difference in separation rates is the most important factor, as women are more likely to fall off the career ladder than men and re-enter the labor market from a lower position. Among high school graduates, women face lower job arrival rates in both employment and non-employment, which slow their upward mobility on the job ladder. Fertility-related interruptions contribute to the search capital channel in both education groups. Since job protection is not universally mandated in the U.S., 30% of high school women and 20% of college women in our data do not return to their pre-birth employers. These women forfeit accumulated search capital and must restart their job search from a lower rung of the ladder after childbirth, which further disrupts their career progression.

Gender differences in turnover patterns not only directly hinder women's search capital and disrupt career advancement, but also lead to wage markdowns from employers. The equilibrium wage-setting channel accounts for 34% and 36% of the gender wage gap for college and high school groups over the fifteen years. Our decomposition suggests three main mechanisms driving the wage markdowns: first, women's shorter match durations due to higher separation rates

[4]This can arise because men and women are often employed in different types of occupations, which offer varying opportunities for skill development and on-the-job learning.

reduce expected profitability for employers; second, lower job-finding rates in non-employment make women more likely to accept lower wages; and third, prolonged childcare leave (averaging 15–17 months for women who do not return to pre-birth jobs) further reduces the match value from the employer's perspective. Notably, women who return to their pre-birth jobs (typically after only 1.8–2.0 months of leave) do not experience significant wage penalties. Their short childcare spells minimize productivity loss and employer concerns, helping them avoid wage discounts. These findings suggest that policies targeting job retention post-childbirth may help reduce the gap, as extended non-employment spells are an important driver of wage stagnation.

The employer responses outlined above are further amplified in settings with rapid human capital accumulation. Women in fast-learning environments are penalized for two reasons. First, they forego more human capital accumulation during career breaks and fall behind their male counterparts faster than in jobs with flatter learning profiles. Second, a stable relationship is even more valuable to firms when employees' productivity grows faster, so employers impose larger wage markdowns on women when the learning rate is high. Neglecting these dynamics substantially understates the extent of employer wage markdowns: for college-educated women, markdowns increase from 20% to 34% when human capital dynamics are incorporated — a 70% increase. These findings illustrate how employer expectations, shaped by anticipated career breaks, can amplify gender disparities in productivity and earnings, particularly for highly educated workers. Recognizing these interactions is crucial for the design of policies targeting turnover and on-the-job training, as well as for interventions tailored to specific labor market segments, industries, or occupations.

This paper contributes both theoretically and empirically to the literature on gender differences in job search and wage outcomes. The model builds on Burdett, Carrillo-Tudela, and Coles (2011) and extends it by introducing child-related non-employment periods. First and foremost, the paper advances the body of work that uses search models to study the gender wage gap (Bowlus, 1997; Bowlus and Grogan, 2009; Flabbi, 2010; Bartolucci, 2013; Morchio and Moser, 2024; Xiao, 2024; Flinn, Todd, and Zhang, 2025). While Xiao (2024) and Flinn, Todd, and Zhang (2025) also model human capital dynamics, we emphasize the role of firms' wage-setting strategies across high- and low-skill environments. By decomposing the sources of gender wage gaps separately for high school and college graduates, the paper highlights how the consequences of women's career interruptions differ across learning environments, particularly when human capital accumulation interacts with worker turnover. These insights inform labor market policies designed to address the distinct challenges faced by workers in different sectors of the economy.

Second, we contribute to the large and still growing literature on the impacts of fertility on the gender wage gap. Prior work documents substantial "child penalties" in women's income and wage trajectories (Angelov, Johansson, and Lindahl, 2016; Kleven, Landais, and Søgaard, 2019). The dynamic frameworks in Erosa, Fuster, and Restuccia (2016) and Adda, Dustmann, and Stevens (2017) examine how fertility influences the gender gap through reductions in women's labor supply and human capital accumulation. In contrast, our focus is on the role of employers' decisions as they anticipate gender differences in caregiving responsibilities. Our equilibrium model incorporates key institutional and behavioral features — such as the likelihood of retaining the pre-birth job, the duration of non-employment spells with and without job protection, and patterns of return to work — to capture how these factors impact wage offers. This framework allows us to pinpoint which dimensions of family-related work interruptions contribute most to the gender wage gap.

Lastly, the paper is also related to the theoretical literature that links women's career interruptions to statistical discrimination by firms (Albanesi and Olivetti, 2009; Gayle and Golan, 2012; Thomas, 2021). In these models, workers have private information about their costs of working during child-rearing years, and employers' uncertainty about workers' types affects who gets assigned to high-paying jobs. We extend this literature by modeling multiple sources of statistical discrimination, including job search and quit behavior, human capital accumulation, and non-participation associated with childbirth. Moreover, the frictional job search framework gives rise to a clear notion of "job ladders," allowing us to analyze firms' wage markdowns at different stages of the career and how these responses interact with workers' skill accumulation.

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

We focus on the period after individuals have completed their education, and follow them for 15 years in the labor market. We exclude individuals who have never worked during the sample period, and we treat the states of unemployment and out-of-the-labor force as the same non-employment state throughout the paper. We focus on two education groups: the group of individuals with maximum 12 to 15 years of schooling are referred to as *high school graduates*, and those who have 16 to 20 years of schooling are *college graduates*.[5] 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.[6]

2.1 Gender wage gaps early in the life-cycle

Substantial male and female wage differentials are apparent 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). To investigate the factors contributing to the gender wage gap and its expansion in this life-cycle period, we first analyze the gap empirically based on the following specification:

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

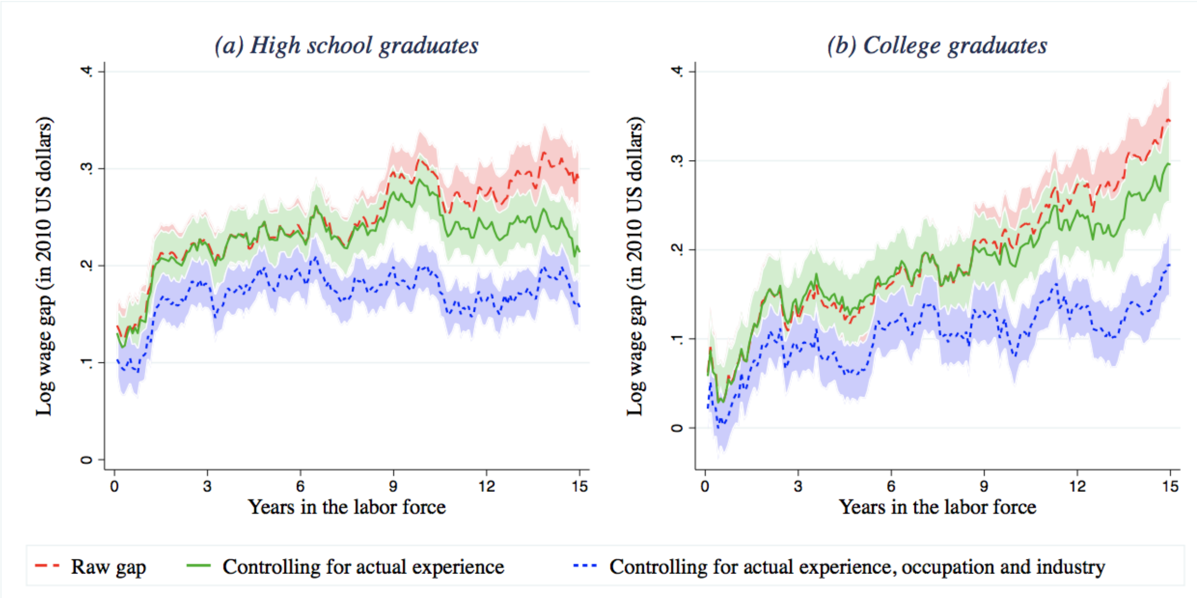
where w_{it} denotes the log hourly real wage of individual i in week t, M_{it} denotes the number of months worker i has spent in the labor force (potential experience), and τ_y are calendar year fixed effects. We decompose the gender wage gap by sequentially adding more controls.

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

[5] 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.

[6] 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 in the first fifteen years after labor market entry*



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.

their interactions in addition to actual experience.

It is perhaps unsurprising that actual experience explains little of the gap in early years of the career, since experience accumulation has not yet started taking place. Adding occupation and industry fixed effects still leaves a substantial portion of the gap unexplained. The "unexplained" gaps are 17 and 9 log-points on average for high school and college graduates, respectively. This suggests that similarly qualified men and women receive unequal pay for doing similar jobs, potentially due to 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. We now document these gender differences in labor market behaviors in our sample.

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*

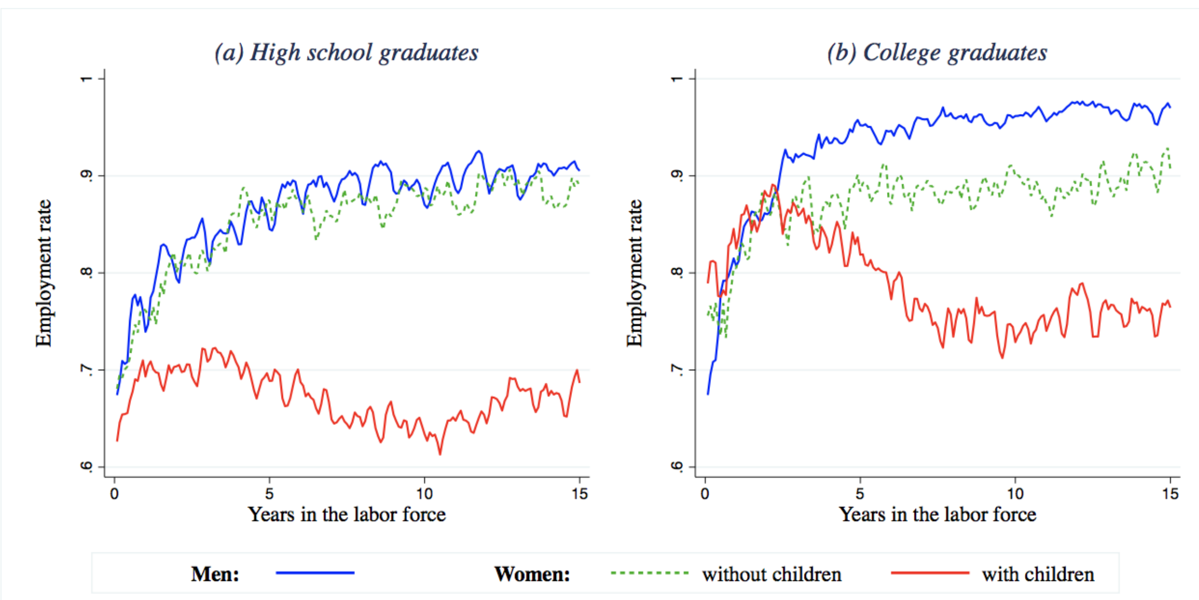
	High school graduates		College graduates	
	Women	*Men*	*Women*	*Men*
Sample size	1331	1376	681	653
Actual experience (years)	10.17	11.69	11.73	12.82
	(4.07)	(3.65)	(3.65)	(3.33)
Number of children	1.49	1.19	1.37	1.28
	(1.18)	(1.14)	(1.21)	(1.24)
Proportion returning to old job after childbirth	69.43%	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.[7] 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 exhibit slightly higher fertility rates than men. Following childbirth, women tend to remain out of the labor force for longer periods 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*



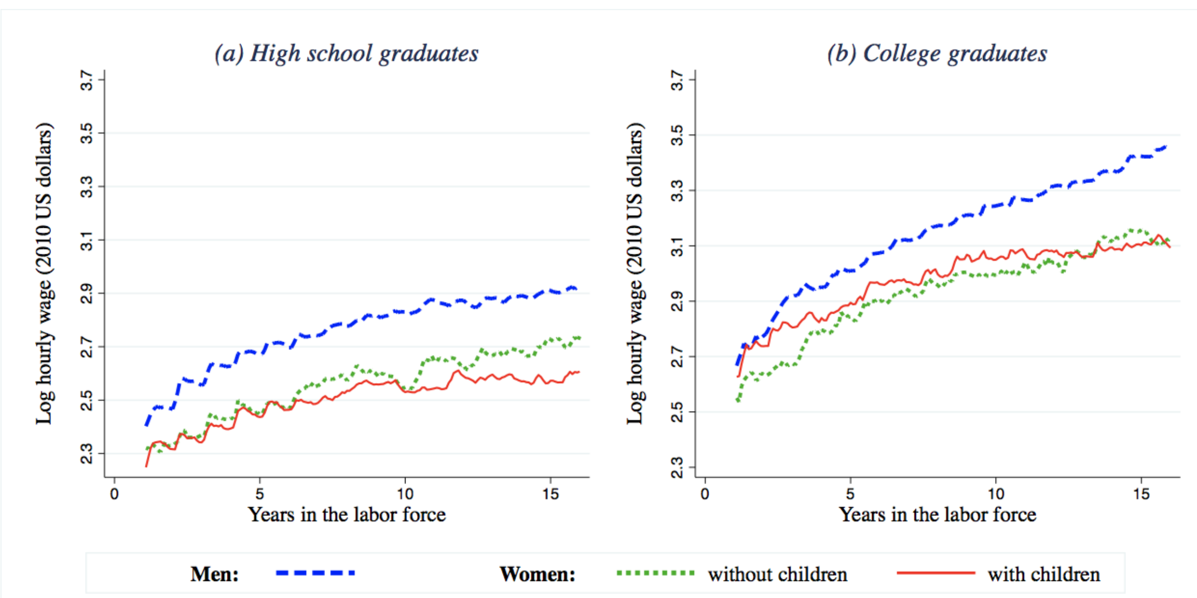
Notes: This figure plots the proportion of workers who are employed during each month after labor market entry. The blue line plots the average monthly employment rate of men, the green dashed line plots that of women who do not have children in our sample period, and the red solid line plots that of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

[7] 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.

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 (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, 2024). Nevertheless, over the course of their careers, childless women accumulate more experience and their wages grow more over time than women with children.

Motivated by the empirical patterns, 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

In this section, we present a dynamic equilibrium model of frictional labor markets with human capital accumulation, fertility-related events, and employer wage-setting.

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 $s \in \{\text{Highschool}, \text{College}\}$ are omitted to keep the notation as simple as possible. In this section, we use "she/her/hers" pronouns to refer to a generic worker in the framework. The structure of the model is entirely synonymous for men and women.

There is a continuum of employers and workers. Throughout the paper, we use the terms *employer* and *job* interchangeably. 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 $y = \varepsilon e^{\rho x}$.

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 $\left[\underline{p}, \overline{p}\right]$.[8] The flow output of the match (y, p) is given by yp. Each employer posts a single wage offer z to all potential applicants, employed and unemployed. The employer's flow profit from a match is $(p-z)y$, and it chooses z to maximize its steady-state expected profits $\pi(p,z)$ across all matches that will form.[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.

If a worker with productivity y accepts wage offer z, she starts working at the job and gets paid a wage $w = zy$. This wage reflects the worker's initial ability ε, her accumulated experience x, the returns to experience ρ, and the wage rate z posted by the employer.[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 in our model are designed to capture key institutional features of the US context, where federally mandated parental leave is unpaid and job protection is not universally guaranteed.[11] Both employed and unemployed workers tem-

[8] The assumption of constant returns to scale implies that workers do not compete for jobs — an employer is willing to hire any worker who finds the offer attractive. As a result, we allow a firm to operate across multiple submarkets, potentially employing both men and women, and both high school and college graduates, if it lies within the support of the firm distribution in those submarkets. However, wage offers are set separately by the firm in each submarket.

[9] Labor market frictions give rise to monopsony power in employers, allowing them to pay wages below marginal productivity. In particular, they pay $w = zy$, where z is some fraction θ of p, implying $w = \theta py$.

[10] For a given employer p, the optimal wage offer z might be different for men and women. Although in practice this type of discriminatory wage is illegal, firms may find ways to circumvent the regulations. In particular, since productivity, y, is unobservable, employers could feasibly claim that women are less productive and offer them lower wage rates. There is also empirical evidence that employers may use unmonitored discretion in wage setting to statistically discriminate women. In the absence of statistical discrimination, transparency laws would not narrow the gender gap in wages. However, the literature consistently finds that the introduction of pay transparency laws significantly raise the pay of women (Baker et al., 2023; Duchini et al., 2020).

[11] The Family and Medical Leave Act (FMLA) provides up to 12 weeks of unpaid, job-protected leave to

porarily exit the labor force upon experiencing a childbirth event, though the duration of this childcare spell may vary. Among those employed at the time of childbirth, a fraction η return to their "old jobs" after childcare leave (the *OJ* state), while the remainder do not retain their jobs and typically face longer career interruptions before re-entering the labor market and beginning to search for new jobs (the *NJ* state). Workers who are unemployed at the time of childbirth also transition into the *NJ* state. If a worker has a subsequent child while in the *OJ* state, she loses the opportunity to return to her pre-birth job and transitions to the *NJ* state. So at each point in time, the worker can be employed, unemployed, or out of the labor force in either the *OJ* or *NJ* state following childbirth.

The distinction between *OJ* and *NJ* leave durations is directly motivated by institutional characteristics of the US labor market. Even after the introduction of the FMLA in 1993, only firms with 50 or more employees are federally mandated to provide job protection, leaving the majority of US establishments exempt from this mandate.[12] Consequently, both the likelihood of retaining a job after childbirth and the length of subsequent labor market interruptions vary substantially across workers. Our model captures this heterogeneity by allowing childcare leave durations to differ depending on whether the worker returns to their previous job.

The probability of returning to the pre-birth job, denoted by η, is taken as exogenous in the model. In practice, this outcome is likely shaped by several factors, including employer policies, worker preferences, and contractual terms. Unfortunately, our data does not allow us to observe whether the decision to return is driven by the worker or the employer. We therefore assume a fixed share η of employed workers retain their jobs after having children.[13] Workers who do not return to their pre-birth jobs (share $1-\eta$) re-enter the labor market as unemployed after an extended spell out of the labor force.

Although it is reasonable to expect that fertility timing, leave duration, and return-to-work decisions might depend on wages, modeling this endogeneity would substantially complicate the analysis. This is because wages are an equilibrium object and such feedback loops could introduce non-stationarity into the economy. We therefore assume that fertility-related decisions

workers in companies with 50 employees or more. By the time of its introduction, in 1993, 80% of our sample had already had their children and small firms (exempt from FMLA) employed around 40% of the workforce. See Bailey et al. (2025) for a comprehensive overview of the FMLA.

[12]Currently, 94.5% of private employers and 54.9% of public employers — together employing about 40% of the workforce — are exempt from the FMLA due to firm size. Although these shares have shifted slightly over time, small employers have consistently made up 90% of US establishments since the early 1990s (Choi and Spletzer, 2012; Henly and Sánchez, 2009).

[13]To our knowledge, no existing US datasets provide information on both fertility events and detailed employment outcomes. We think of η as reflecting the decentralized, uncertain nature of job protection in the US, where workers and employers historically lacked clarity about post-childbirth retention.

are primarily shaped by social norms and family leave policies, rather than being highly responsive to wage offers. This assumption has implications for the interpretation of our counterfactual results, which we discuss in Section 5.3.

3.1 Workers' Behavior

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

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

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

The flow payoff of the worker is by, which reflects her value of leisure or home production. She gets a job offer (that is, she sees the vacancy posted by 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 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

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

The worker enjoys a flow payoff that is her wage zy. Because of human capital accumulation, the value of employment grows by the amount $\rho y \partial V(y,z)/\partial y$. There is on-the-job search, so the worker receives job offers at rate λ_e and moves to a new 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

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

While on leave, the worker gets her flow utility $b^{out}y$, which reflects her value of time with a newborn child. The worker remains "out of the labor force" until the spell at home with the baby ends, at rate γ_2, upon which she will resume her previous job. We interpret γ_2 as related to the average number of months of job protection provided by 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

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

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

The assumption that the flow wage w is log-linear in accumulated experience x substantially simplifies the solution to the differential equation (3).[14] We show in Appendix C.1 that 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.[15]

[14]The log-linear functional form facilitates analytical solutions but cannot capture the flattening of wage profiles at later stages of the career, as documented by Manning (2003). Our analysis focuses on early career dynamics, where most of the widening in the gender wage gap takes place (Goldin, 2014; Barth et al., 2021). Extending the framework to later career stages is an important direction for future research.

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

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*

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

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 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.[16] 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.

[16] 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

3.2 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.

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

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

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 $\{z^R, m_E, m_U, m_{OJ}, m_{NJ}, H(\cdot), N(\cdot), N^{OJ}(\cdot), N^{NJ}(\cdot), H(\cdot,\cdot), H^{OJ}(\cdot,\cdot), F(\cdot), \xi(p)\}$ for all $\varepsilon \in [\underline{\varepsilon}, \overline{\varepsilon}]$ and all $p \in [\underline{p}, \overline{p}]$ 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 $p \in [\underline{p}, \overline{p}]$, 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 targeted moments. We provide an intuition for identification in several steps. First, since human capital is general and remains the same when carried over to a new job, the wage change during a job-to-job transition is only related to the changes in human capital prices (the z's) offered by different firms. Therefore, targeting both such wage changes and the overall 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 [17] 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 3 shows the estimates of jointly estimated GMM parameters and their standard errors. All parameters are precisely estimated. We provide the details of the GMM procedure and the computation of standard errors in Section D.2.

The estimates of the human capital accumulation rate show that college men have a much higher ρ than college women, but high school men and women have very similar accumulation

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

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.

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

Table 3: Jointly estimated parameters

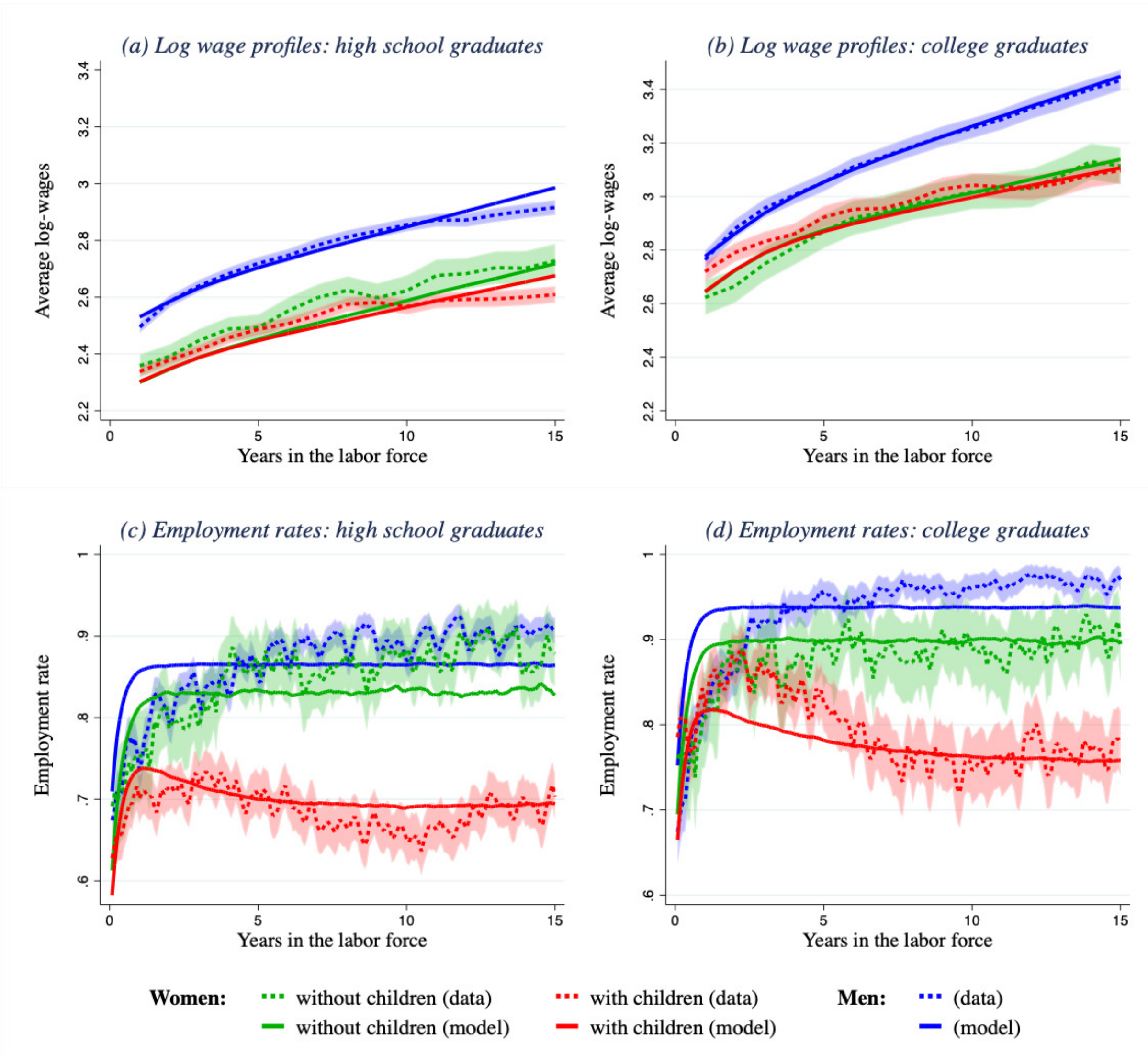
		High school graduates		College graduates	
		Women	*Men*	*Women*	*Men*
$\boldsymbol{\rho}$		2.614×10^{-3}	2.647×10^{-3}	2.324×10^{-3}	3.196×10^{-3}
		(0.067×10^{-3})	(0.094×10^{-3})	(0.079×10^{-3})	(0.072×10^{-3})
$\boldsymbol{\Gamma}(p)$	$\underline{p}$	6.024	6.704	4.961	6.166
		(0.294)	(0.181)	(0.122)	(0.075)
	$\overline{p}$	19.999	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	99.999	17.371	13.729
		(0.012)	(3.684)	(1.479)	(4.203)
$\boldsymbol{A}(\varepsilon)$	α_1	1.314	1.152	1.650	1.399
		(0.036)	(0.027)	(0.067)	(0.034)
	α_2	0.880	0.881	1.340	1.415
		(0.032)	(0.052)	(0.043)	(0.025)
$\boldsymbol{b}$		7.398	9.855	5.888	8.258
		(0.087)	(0.166)	(0.177)	(0.135)

Notes: This table reports the point estimates of the jointly estimated parameters via GMM 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.

within skill groups are moderate — about 0.1 log points in favor of men in the low-skill group, and about 2 log points in favor of men in the high-skill group. We interpret these gender differences in initial productivities as residual gaps accounted for by a number of factors that we do not model explicitly, such as choice of major and quality of degrees, initial cognitive and non-cognitive skills, and taste-based discrimination (in the labor market or during schooling years).

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

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.

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 gender pay gap dynamics 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 time.

5.1 Decomposing the 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 $s \in \{\text{High school, College}\}$ 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.[18]

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

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

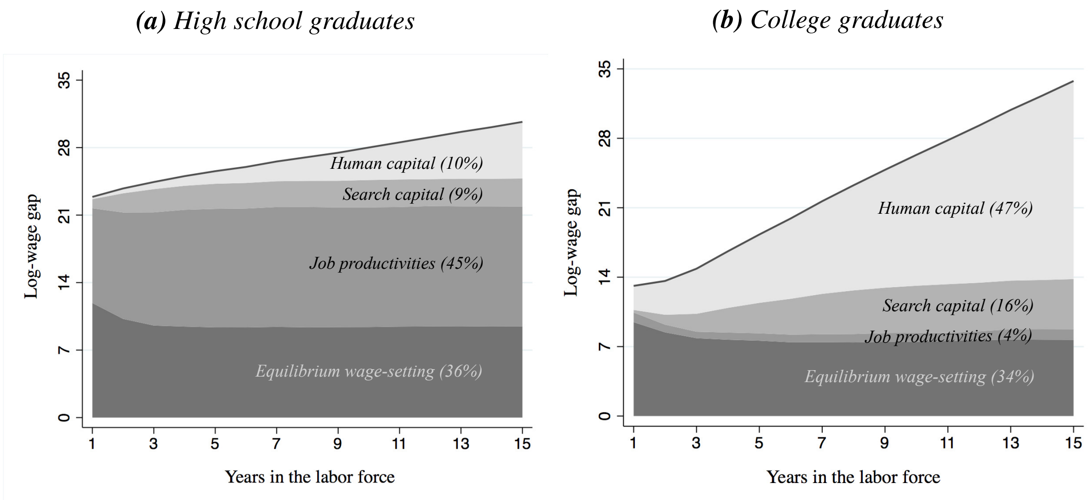
Equation (13) decomposes the gender wage gap at any given point of workers' careers into the following four additive channels: *i)* the *human capital channel* captures the difference in wages arising because men tend to accumulate more experience on-the-job than women and also might have a higher productivity 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. [19]

Figure 5 illustrates the relative importance of these four components over potential experi-

[18] 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).

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

Figure 5: *Decomposition of the gender wage gap*



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.

ence. 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.[20]

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

[20]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.

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 *expansion* of the gender gap, it is worth noting that the 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 early in workers' careers, 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 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.[21] We discuss early 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 the expansion of 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,

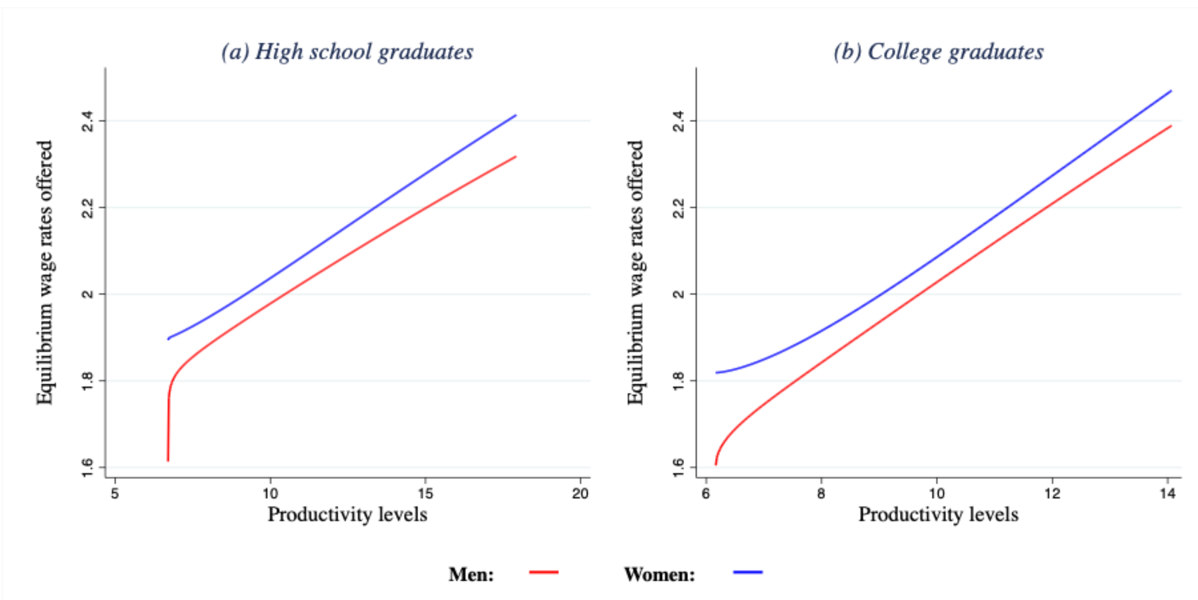
[21] Barth et al. (2021) find that differential progression within-establishment is the major driver of the gender gap expansion for college-educated workers, whereas it matters less for the gap expansion in the high-school group.

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.

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.

On average, women would get wage offers that are 13 and 10 log points lower than men in the high school and college groups, respectively. There is also considerable variation in the size of these gender gaps across the job productivity distribution. In both groups, the wage discounts towards women are much more pronounced in low-productivity jobs than in high-productivity jobs — the gap is 28 log points in the bottom firms compared with 10 log points in top firms for high-school graduates. For the college group, the differences between offers in low- and high-productivity firms are somewhat milder — 21 and 8 log points, respectively.

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.

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 3.5 log points if their quit rate δ were reduced to men's level.

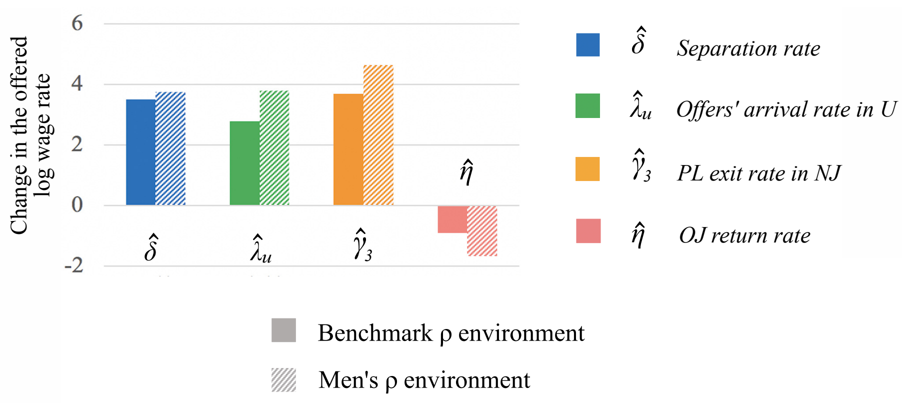
Both high school and college wage offers are driven by fertility parameters in similar ways. If women in the *NJ* state were to return to the labor market as fast as men, their average offered wage rates would increase by 1.1 and 3.7 log points in the high school and college sectors, respectively. Since 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 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

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.

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 time.

5.3 Evolution of the gender wage gaps

Recall that at each point in time, 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 early 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 women's wages).

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

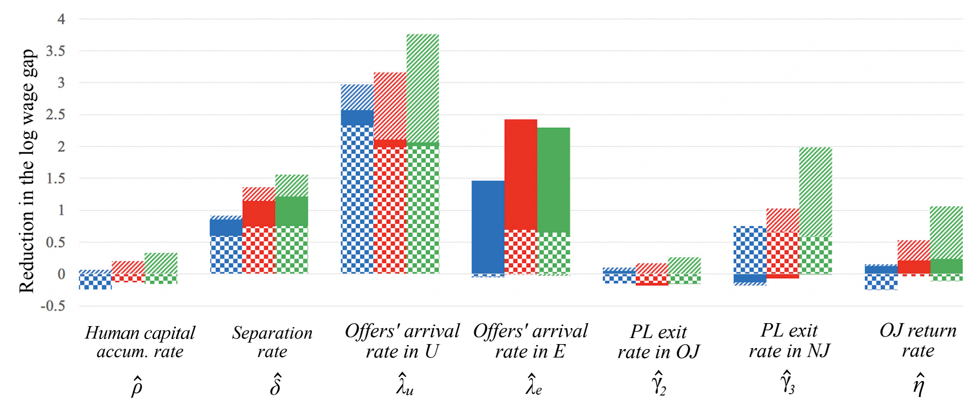
		High school graduates	**College graduates**
Human capital accum. rate	ρ	0.03	2.89
Separation rate	δ	1.28	7.92
Offers' arrival rate in *U*	λ_U	3.30	1.71
Offers' arrival rate in *E*	λ_E	2.04	0.00
PL exit rate in *OJ*	γ_2	0.02	0.09
PL exit rate in *NJ*	γ_3	1.17	1.98
OJ return rate	η	0.45	0.27
Average log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

Notes: The table shows the average increase in women's wages over time (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.

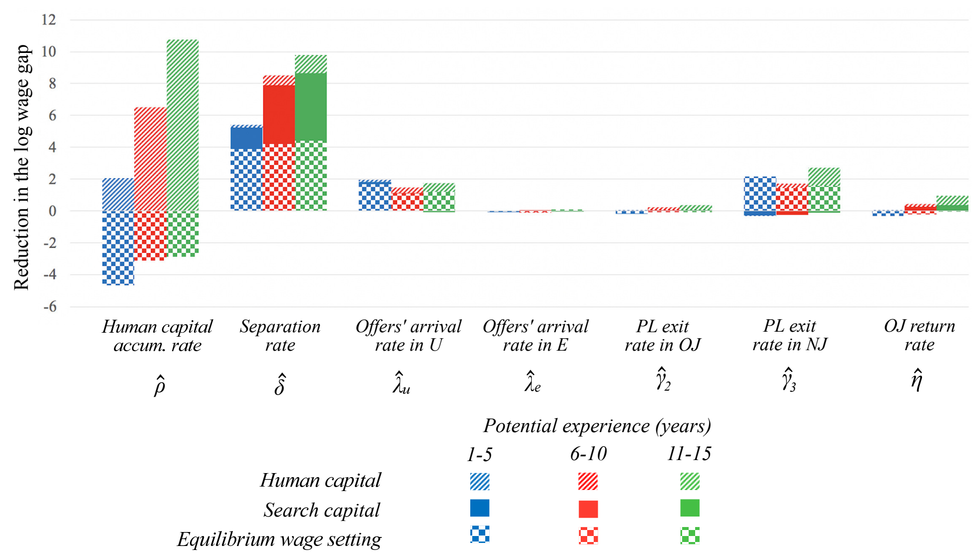
For high school graduates, the early life-cycle wage gap between men and women is driven mainly by gender differences in job search and fertility interruptions. The low job-finding rate λ_u not only leads to a significant discount towards women in the wage-setting process but also hinders women's human capital accumulation relative to men, which becomes especially

Figure 8: *The effect of each parameter on the gender wage gap at different points of early career*

(a) *High school graduates*



(b) *College graduates*



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.

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 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 expansion of the 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.

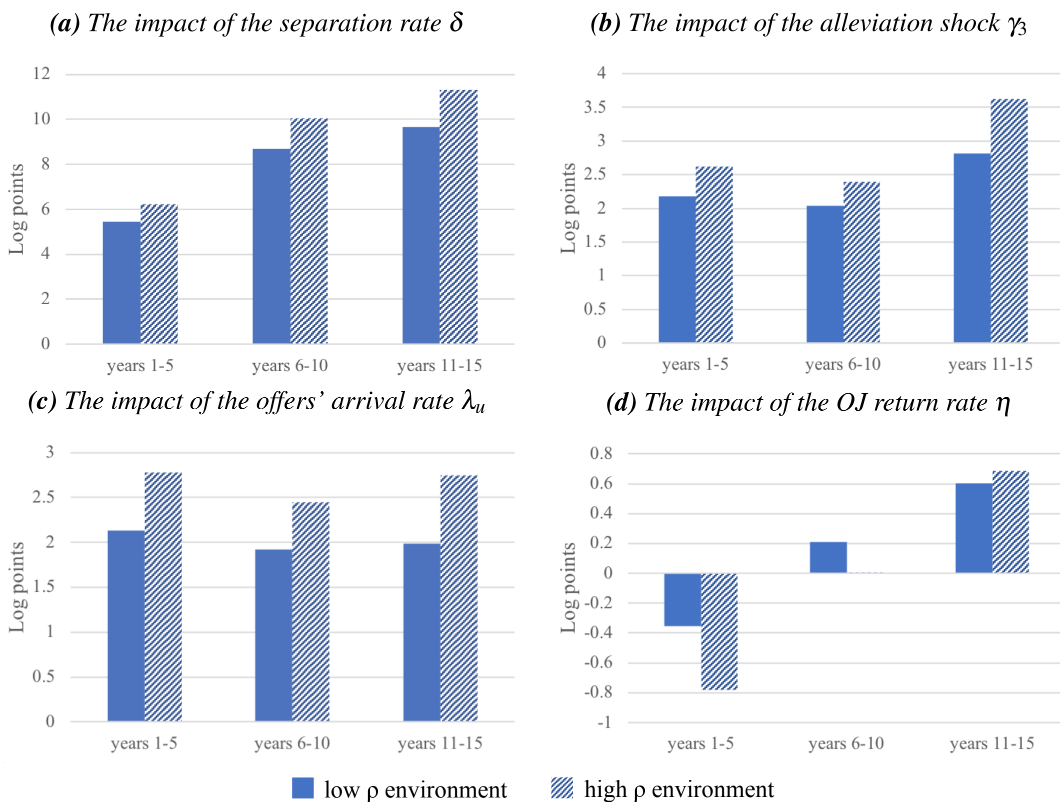
We show in Section 5.2 that firms' wage-setting responses to gender differences in turnover are magnified in work environments with more intensive learning on-the-job. Over time, additional dynamic interactions emerge between turnover and human capital accumulation because improved employment stability 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 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 early career 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 gender wage gap expansion 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.

Figure 9: *The dynamics 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.

6 Conclusion

This paper studies the dynamics of the 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 gender disparities in wage trajectories are 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 wage-setting practices we model are illegal, wage discrimination is often difficult to detect in practice, as firms may find ways to circumvent regulatory scrutiny. For instance, since individual productivity is unobserved, firms can plausibly justify lower wages for women by claiming they are less productive. Employers may also relabel job titles to obscure direct comparisons between male and female workers, or argue that men face greater poaching risk and must be paid more to retain.

These challenges highlight the value of a structural framework that disentangles unobserved productivity from employer wage-setting behavior. While our model interprets differential wage offers as firms' rational responses to gendered labor market patterns, this should not be taken to imply that such outcomes are socially acceptable. Employers may not depart from profit-maximizing strategies, but well-designed policies can still shape women's turnover behavior — and, in turn, influence labor market outcomes through firms' endogenous responses.

An important factor behind employer wage markdowns, especially for college-educated women, is the prolonged non-employment experienced by mothers who do not (or cannot) return to their pre-birth jobs. These long interruptions contribute significantly to gender gaps in equilibrium wage offers. Policies that reduce the length of these career breaks — for instance, by supporting job retention or facilitating re-entry — can help narrow gender wage disparities over the course of the career. Beyond fertility-related factors, our results highlight the importance of improving women's labor market stability more broadly. For college graduates, equalizing women's separation rates to those of men would close the wage gap by an average of 34% over the first 15 years of the career. For high school graduates, closing the gender gap in job-finding rates would reduce the wage gap by 12% over the same period.

A key insight of the model is that the large impact of turnover differences on wage outcomes is largely driven by their interaction with human capital accumulation. The intuition is twofold: 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 total gender wage gap.

Our analysis highlights several promising directions for future research on gender inequality. First, our model focuses on utility from wages and is silent on the potential value that workers (and their children) may derive from time spent at home. Career interruptions related to caregiving may yield private or social benefits that are not captured by wage-based measures alone. Thus, policies that raise wages by shortening childcare spells may not necessarily improve workers' and children's long-term welfare. Addressing this limitation would require a richer model of household utility and child outcomes — an important step toward more comprehensive welfare analysis.

A second area involves extending the model to cover a longer span of workers' careers. This would require a more flexible wage process for later career stages. The log-linear specification we adopt is well-suited for early-career dynamics where most of the gender gap widening occurs (Goldin, 2014; Barth et al., 2021), but does not capture the wage profile flattening typically observed at older ages. While such extensions are beyond the scope of the current paper, we view our framework as a first step toward understanding how employer wage-setting interacts with career interruptions over time.

Finally, a natural next step is to model the feedback loop between workers' fertility-related decisions and wage offers. Our framework focuses on how firms respond to exogenous changes in workers' quit rates, leave durations, and return-to-work probabilities. However, shifts in wage offer distributions across genders may, in turn, also influence household decisions around the division of parental leave and childcare responsibilities. These propagating effects could amplify the long-run impact of gender equity policies, suggesting that our counterfactual results may represent a lower bound. Quantifying the feedback mechanisms remains an important direction for future research.

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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.[22] The data in Waldfogel (1999) show that no more than 40% of employees in medium to large firms[23] (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.

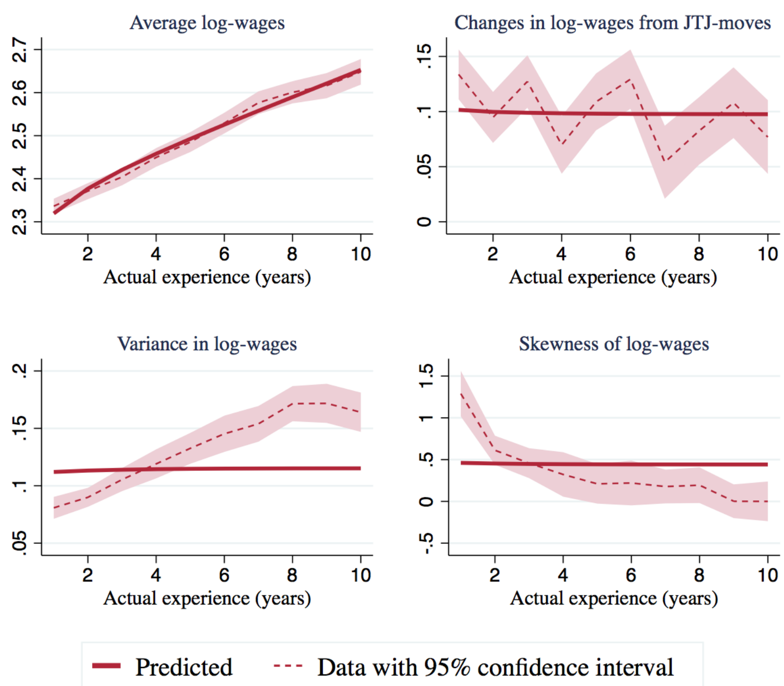
[22] Only six states (California, Connecticut, Massachusetts, Minnesota, Rhode Island, and Washington) required at least some private sector employers to offer maternity leave coverage prior to 1988. See more details about US maternity leave policies in Berger and Waldfogel (2004).

[23] 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*

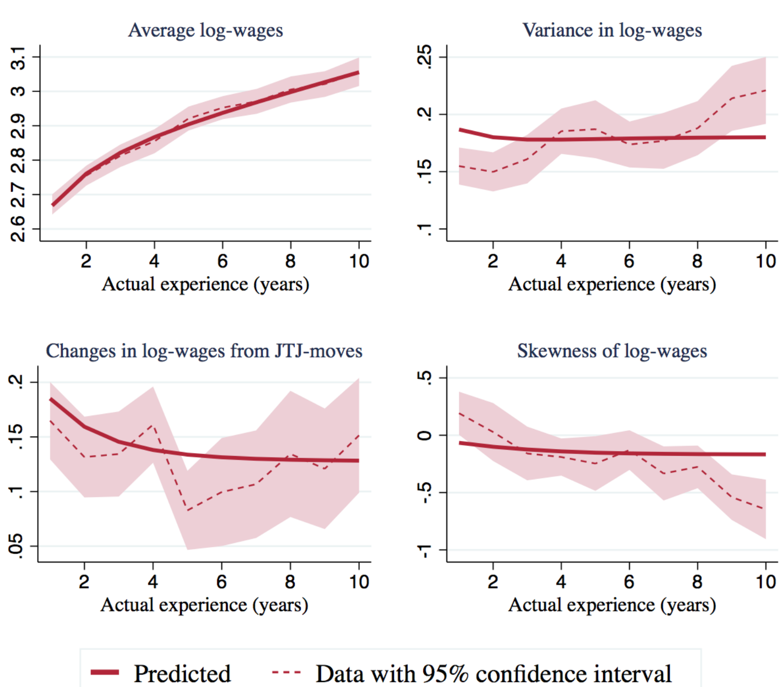
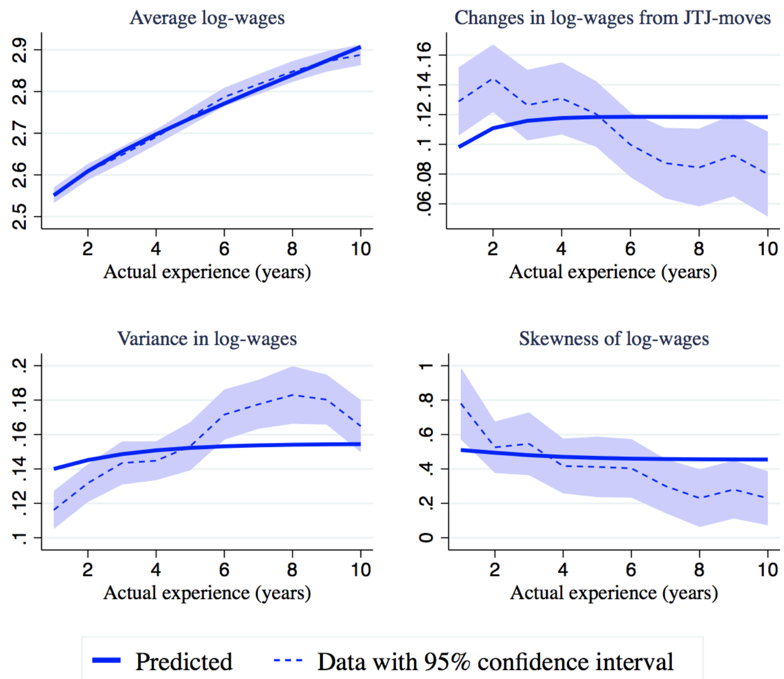
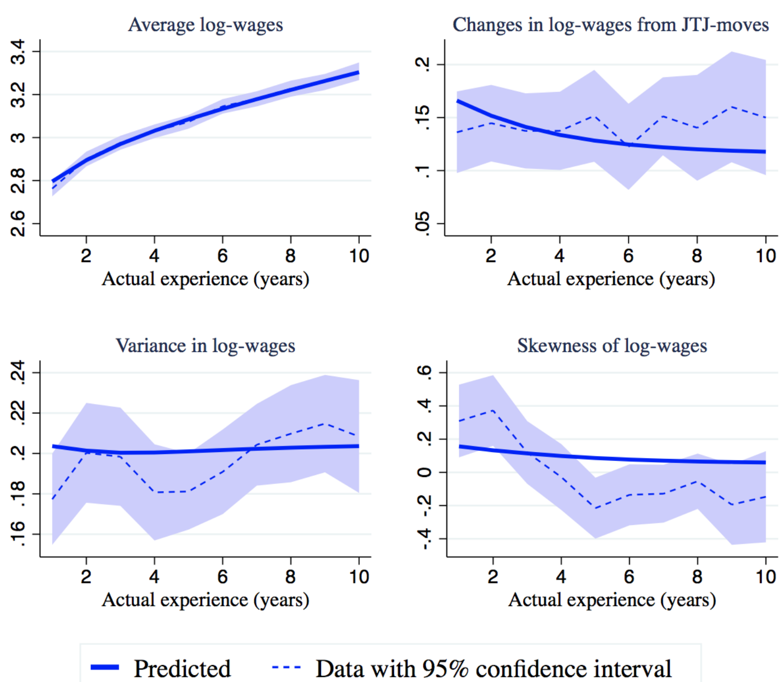


Figure B.2: *Fit of the targeted moments in GMM estimation for men*

(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

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

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

C.2 Derivations: Worker's Side

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

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

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

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

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

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

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

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

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

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

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

With the boundary condition

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

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

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

and

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

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

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

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

C.3 Characterization of Steady-State Measures and Distributions

Proposition 2 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) $H(x,z)=\frac{m_U}{m_E}\lambda_u F(z)\left(\frac{1}{s(z)}\left(1-e^{-s(z)x}\right)-\left(1-\frac{R_1}{\lambda_U}\frac{m_E}{m_U}\right)\frac{1}{s(z)-R_1}\left(e^{-R_1 x}-e^{-s(z)x}\right)\right)$ *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

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

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

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

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

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

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

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

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

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

$\gamma_1 m_U N(x) + (1-\eta)\gamma_1 m_E H(x) + \gamma_1 m_{OJ} N^{OJ}(x) = (\phi+\gamma_3)\,m_{NP} N^{NP}(x)$, and *ix*) The flows into and out of employed pool with experience below x and wage rate below z balance

$\lambda_u m_U N(x)F(z) + \gamma_2 m_{OJ} H^{OJ}(x,z) = q(z) m_E H(x,z) + m_E \frac{dH(x,z)}{dx}$.

x) The flows into and out of OP-pool with experience below x and wage rate below z balance

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

The first four equations *(i)-(iv)* in the system above solve for the four unknowns m_U, m_E, m_{OJ}, m_{NP}. Then, the remaining six equations *(v)-(x)* solve for the six unknowns $N(x)$, $H(x)$, $N^{OJ}(x)$, $N^{NP}(x)$, $H(x,z)$, and $H^{OJ}(x,z)$, 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

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

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. $\square$

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,

$$\int_{z^R}^{\bar{z}}\frac{(1-F(z))}{\left(q(z)+r-\rho-\frac{\eta\cdot\gamma_1\cdot\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}dz=\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\xi'(x)dx.\text{[24]} \tag{28}$$

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),

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

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

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

□

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 $F(z)$.[25] 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

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

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

[25] 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

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

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

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

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

which does not depend on F. Thus,

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

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,

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

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

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

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

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

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

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

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

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

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

so that

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

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

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

and hence

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

D.3.4 Skewness

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

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

D.3.5 Kurtosis

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

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

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

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