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EQUILIBRIUM WAGE-SETTING AND THE LIFE-CYCLE GENDER PAY GAP

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July 20, 2020

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Abstract

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JEL-codes: J16, J24, J31, J64.

Keywords: Gender wage gap, life-cycle, firm heterogeneity, human capital, job search.

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1 Introduction

The gender wage gap has been a persistent phenomenon even in the world's most developed economies. Despite the gender convergence in labor force participation, education and occupational composition in the US, women's wages have plateaued at below 80% of men's since the 1990s. Moreover, almost half of this wage gap is still "unexplained" — men and women are offered different wages even when they have similar education, experience backgrounds, and work in the same occupation and industry (see Figure 2). In this paper, we focus on the labor demand side as an explanation for this "unexplained" portion of the gender wage gap. We highlight employers' wage-setting decisions as potentially overlooked factors to be addressed in order to eliminate gender inequality completely.

Men and women differ in many dimensions in the labor market. For example, they might have different job mobility patterns, and women might have weaker labor force attachment than men due to family responsibilities. Weak attachment and short match durations are costly for firms in the presence of search frictions, because meetings between workers and firms are sporadic and it takes time to form a new match. Therefore, profit-maximizing employers might transfer expected future costs of turnover into lower wage offers towards women. In addition to that, firms also take into account workers' considerations and their reservation wages in a labor market equilibrium. These endogenous feedbacks between the demand and the supply sides of the market can both enhance or counteract the intended impact of policies aimed at reducing gender disparities. Therefore, it is important to understand the mechanisms underlying firms' wage-setting decisions, so that policies can target the gender issue at its sources.

In this paper, we quantify both labor supply and demand channels underlying the life-cycle gender wage gap. On the labor supply side, workers accumulate human capital only when employed. For example, having a higher quit rate implies that women spend more time in non-employment, accumulate less experience on the job and become less productive than men over time. On the labor demand side, we consider firms' differential wage rates for men and women for each unit of human capital. For example, if employers anticipate higher quit rates from women, they would consider the costs associated with shorter match durations and thus discount women's wages. The quit probability is just one example of the many dimensions of gender differences we examine in this paper, and each of these dimensions might contribute to the wage gap through both worker- and firm-side factors.

Such demand and supply forces might operate in different ways in low-skill and high-skill labor markets, given the difference in job search behaviors and the different natures of the jobs in these sectors. In the low-skill sector, turnovers are generally more frequent for both men and women, the job ladder is more compressed and there is less scope for career advancement. In the high-skill sector, there is potentially more learning-by-doing on the job, wages are more dispersed, and women are more likely to face a "glass ceiling." It is thus natural for us to study the gender wage gap separately in these two markets. We develop an equilibrium search model in order to quantify the extent to which different gender dimensions affect the life-cycle wage gap in both low-skill and high-skill groups.

The model features wage-posting by employers, human capital accumulation by workers through learning-by-doing, and on-the-job search. Labor markets are segregated by gender and education. Within each gender-education group, workers are heterogeneous in initial human capital, and firms are heterogeneous in productivity. We also incorporate several dimensions of gender differences within each education group, including the job-finding rate, job-to-job transition rate, separation rate, human capital accumulation rate, and the fertility process. We allow for taste-based discrimination as a residual component.

Upon exogenous fertility events, both men and women go into a period of non-employment (parental leave) where there is no job search, no contribution to firm output and no human capital accumulation. To reflect the institutional setting in the US during our data period, parental leave is unpaid and only a fraction of employers provides job protection. Fertility rates, parental leave durations and the probabilities of receiving job protection all differ by gender and education.

One key feature of the model is that the individual wage is a product of the worker's accumulated human capital and the price paid by her current employer for each unit of the worker's human capital. At any point in time over the lifecycle, women's average wage might be lower than that of men either because of productivity differences (in human capital levels) or differences in the average price received. Note that the average prices could be driven by two mechanisms. First, the same firm may offer different prices for men and women as a result of profit maximization, as it considers group-specific turnovers, fertility interruptions and human capital accumulation rates. We refer to the endogenous price distributions by gender as wage ladders that workers climb throughout their careers, and they are key components of the frictional equilibrium. Second, the process of on-the-job search allows workers to gradually improve their positions on the wage ladders. So even if women and men climb the same job ladder, women might lag behind because they are less likely to transition from job to job than men, and are more likely to fall off the career ladder.

This way of setting up human capital levels and prices not only allows us to obtain a tractable analytical solution to a complicated dynamic equilibrium model, but also offers insights into the complementarity of the two channels contributing to the gender wage gap. On the firm side, although offering a higher human capital price reduces profits per worker, it also allows the firm to attract and retain workers with higher human capital levels. The increase in profits from a more talented workforce is especially important for more productive firms, because firm productivity and its human capital composition are complementary in production. On the worker side, anticipating higher (or lower) human capital levels in the future makes the individual willing to accept a lower (or higher) wage rate to start with. These reservation values are in turn taken into account by the firms when setting wages. Human capital levels and prices are thus inter-dependent, and our unified framework that includes both channels allows us to study their rich interactions.

While it is common to evaluate the impact of a policy on workers' human capital levels, the consequences on prices are often less straightforward. On the one hand, policy changes might alter the relative attractiveness of employment versus unemployment for workers. Given the distribution of available job opportunities, workers might change their reservation wages in response to better (or worse) employment prospects in the future. On the other hand, firms might also respond to new policies by raising or lowering wage offers. The direction of firms' responses might depend on how the new policy affects the skill composition of the working population, the intensity of competition between firms, the new wages set by other firms in the economy, and the (equilibrium) reservation wage of workers.

Compared to previous literature, our model offers further insights into the gender wage gap at different points of the firm productivity distribution. Low-productivity firms rely heavily on hiring from non-employed workers, and thus respond strongly to the reservation wage rates of the non-employed. Instead, high-productivity firms rely mostly on poaching from the pool of employed workers, and these workers contribute to a more productive workforce in firms at the top. As a result, match stability is more valuable for high-end firms because they lose more flow output in the case of match termination. Therefore, top firms are willing to raise wages more than low-end firms in response to a higher job-to-job transition rate for example. This might potentially lead to a "glass ceiling" effect whereby high-end jobs reward men more in order to better retain them as they face many outside offers.

Using the 1979 National Longitudinal Survey of Youth (NLSY79), we first document the gender differences within high school graduates and college graduates. Focusing on the first fifteen years of workers' career since labor market entry, we find that women who graduated college are much more likely to transition into unemployment than men (58% more), while their probability of finding a job in unemployment and of transitioning to another job are somewhat similar. For high school graduates however, gender disparities take different forms. Low-skilled women have a much lower job-finding rate in unemployment than low-skilled men (24% lower), while separation rates and job-to-job transition rates are comparable. For both college and high school groups, women spend more time on parental leave than men. However, workers in the college group generally go back to work sooner than those in the high school group.

We estimate the model on NLSY79 data using Generalized Method of Moments. Based on the model estimates, we conduct counterfactuals to decompose the gender wage gap into four additive channels. First, the *human capital channel* captures the difference in productivity gains during employment through learning by doing. Second, the *job segregation channel* reflects productivity differences between firms employing men and those employing women. Third, the *search capital channel* captures the fact that women's different turnover patterns make them progress through the job ladder at a different pace than men. Fourth and last, the *equilibrium wage setting channel* measures the difference in the prices offered to men and women by the same firm for each unit of human capital.

We find that firms' wage setting channel is a main source of the gender wage gap for both high and low education groups. Differential wage offers by gender accounts for 55% of the gap for high school graduates and 47% for college graduates. The human capital channel is also important, accounting for 23% and 32% of the gap for high school and college groups, respectively. The human capital channel plays a bigger role later in the life-cycle especially for college graduates, whereas the wage-setting channel explains almost the entire gap at the beginning of the life-cycle.

We further analyze the driving factors of the gap by quantifying the relative importance of each of the dimensions in which men and women differ in the model. We find that improving the stability of women's employment has the largest effect in narrowing the gender gap. In particular, for college graduates, eliminating the gender difference in the separation rates reduces the wage gap by 50% on average. For high school graduates, equalizing job-finding rates across genders reduces the wage gap by about 25% on average. For both groups, equalizing fertility related career interruptions would reduce the gap by approximately 19%. These reductions are a combination of two effects: first, eliminating gender differences in labor market or fertility related transitions would allow women to gain more human capital and thus receive higher wages, especially later in their career; and second, firms would adjust their expectations towards men and women, and offer more similar wage rates to both genders throughout the life-cycle. The second effect is quantitatively more important than the first for both education groups.

Interestingly, we find that increasing women's within job wage growth (the human capital accumulation rate in the model) would only have a modest effect on the life-cycle wage gap. Albrecht, Bronson, Thoursie, and Vroman (2018) suggests that closing the within-firm promotions gap across genders would be an effective policy to reduce gender inequality. However, the story is more nuanced through the lens of our model. We find that college men's return to experience is 43.4% higher than that of college women, but increasing women's human capital accumulation rate would in fact widen the gender wage gap by 24% in early career because women would be willing to accept lower starting wages in return for a better accumulation technology. In the long run, however, the gains in the human capital stock would more than compensate for the initial loss in wage rates, so the net effect on women's wages would be positive in late career, reducing the wage gap by 12% and 25% in years 6–10 and 11–15 respectively.

Finally, the human capital accumulation rate creates sizable interactions with the rest of the gender differences. In particular, increasing the returns to experience amplifies the effect of an increase in employment stability. This is because when human capital accumulates faster, any increase in work experience due to more stable employment would lead to a larger increase in the human capital stock. At the same time, firms value match stability more when employees' productivity grows faster, and they respond in favor of a higher distribution of wage rate offers. We find that equalizing job- or fertility-transition rates together with an increase in the human capital accumulation technology leads to a combined effect on the gap that is 17% larger than the sum of their separate effects for the college group.

To the best of our knowledge, we are the first to study the gender wage gap in terms of the price-quantity decomposition, and to incorporate equilibrium firms' wage-setting as one of the main factors driving human capital prices. We illustrate how prices are formed, and how they respond to differences in frictions and human capital accumulation technology, and we show how the human capital stock is built resulting from accumulation technology and frictions. We elaborate more on our contributions to the literature in the next section.

1.1 Related Literature

A recent empirical literature on the gender wage gap has focused on quantifying the relative importance of within and across job wage changes using matched employer-employee data. Goldin et al. (2017) and Barth, Kerr, and Olivetti (2017) find that differences in within job wage growth are more salient for college-educated workers in the US context, and for high school-educated workers both channels have a quantitatively similar role. Card, Cardoso, and Kline (2016) find that in Portugal, sorting across firms plays a larger role for low- and middle-skilled workers. Motivated by the different findings across education groups, we also analyze high and low-skilled markets separately. Our paper provides a structural counterpart to this recent empirical literature. We contribute to this literature by uncovering the mechanisms behind the observed gap and evaluating a rich set of counterfactual policy exercises.

There is a large literature that focuses on the impact of fertility on the gender wage gap. Angelov, Johansson, and Lindahl (2016) and Kleven, Landais, and Søgaard (2019) compare the income and wage trajectories of women to those of their male partners to quantify the penalty of having children. Both studies find sizable child penalties. Erosa, Fuster, and Restuccia (2016) and Adda, Dustmann, and Stevens (2017) develop dynamic models of human capital accumulation, fertility and labor supply choices of women to estimate the impact of children on the gender wage gap. These papers document the motherhood penalties, focusing on decreases in labor supply and human capital depreciation. In contrast, we consider the role of employers in labor market equilibrium. We find that these endogenous firm responses to expected fertility behavior account, in fact, for the bulk of the impact of fertility-related gender differences on the life-cycle wage gap, especially at the early stages of a career.

The role of turnover differences across gender in frictional labor markets has been explored from a number of angles. Early literature focused on mechanical effects of career interruptions (Manning (2000), Manning and Robinson (2004), Del Bono and Vuri (2011)). Based on a seminal book by Manning (2003), other researchers argued that frictions and gender differences in mobility patterns lead to varying degrees of monopsony power that each firm has towards male and female workers, lowering women's wages (Barth and Dale-Olsen (2009)). Bowlus (1997), Bartolucci (2013)) and Moser and Morchio (2020) use a Burdett-Mortensen-type model to analyze the gender gap in wages that emerge in equilibrium as a result of differences in labor market turnover across genders. We contribute to this strand of literature by including human capital accumulation over the life-cycle and distinguishing between both the mechanical effects of interruptions on the worker side, and the equilibrium wage-setting responses of the firms to these expected interruptions.

Frictions alone cannot explain the entire life-cycle gender wage gap. As has been found by a voluminous literature (see Blau and Kahn (2016) for a comprehensive review), differences in human capital variables account for a sizeable portion of the gap. Bagger, Lesner, and Vejlin (2019), and Xiao (2019), link the life-cycle gender gap to both human capital and the role of firms in a frictional labor market. In contrast to them, we focus on the distinct roles of human capital levels and human capital prices in the gender wage gap at different stages of the life-cycle. We show that this price-quantity distinction is instructive and meaningful when applied to the gender-wage-gap decomposition. Extending Burdett, Carrillo-Tudela, and Coles (2016), our work sheds light on the mechanisms behind both gap components in a transparent and tractable way, and highlights the importance of firms' endogenous wage policies for the gender gap in human capital prices. We do this separately for low- and high-skill segments of the population, highlighting the forces that shape careers in these two different markets.

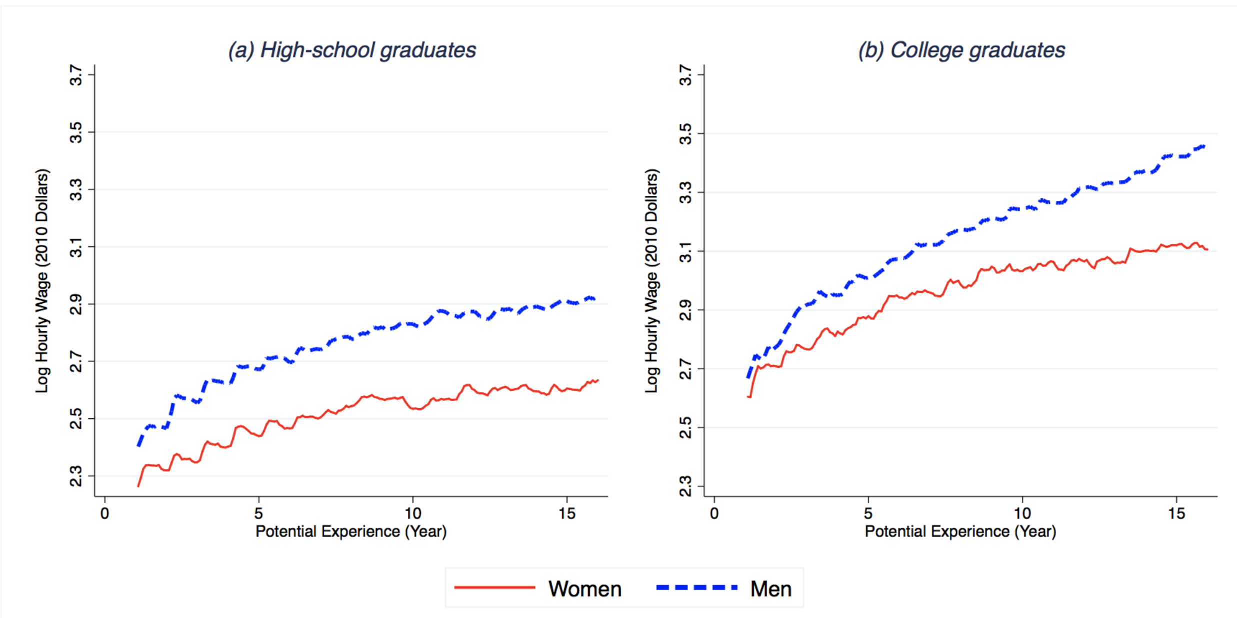
In the next section, we describe the data we use and provide evidence of differential wage growth between men and women. In Section 3, we describe the model. Section 4 describes the estimation strategy, Section 5 details our results and Section 6 concludes.

2 Data

Our data comes from the National Longitudinal Survey of Youth 1979 (NLSY79), an annual longitudinal dataset following the lives of 12,686 respondents who were between the ages of 14 to 22 in 1979. Individuals 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 transition, occupation and industry, hourly wage, and number of hours worked.

We include data for individuals after they have completed their education, and follow them for 15 years in the labor market. 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." In order to avoid confounding gender disparity with racial disparity, we restrict our sample to non-black, non-Hispanic individuals. We also restrict the sample to individuals who did not have any child while in school. These restrictions leave us 1,376 men and 1,331 women in the high school group, and 653 men and 681 women in the college group.[1]

Figure 1: *Male vs. Female Hourly Wage Profiles Over the Life-cycle, by week*



Notes: The lines in the figures above, represent the average log hourly wages of men and women in each month after labor market entry.

2.1 Gender wage gaps over the lifecycle

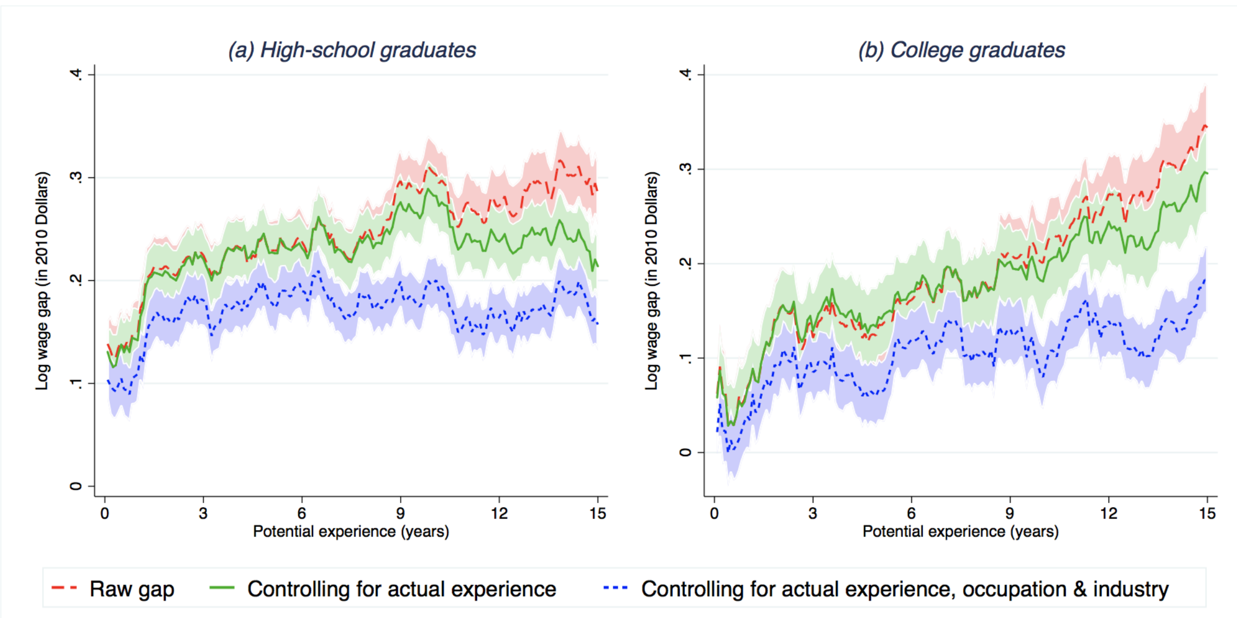
Figure 1 shows the average log hourly wages of men and women by potential experience, for high school and college groups respectively. The series are at monthly frequency, and the horizontal axis indicates years in the labor market. Substantial male and female wage differentials exist even at the beginning of workers' careers. The initial wage gap is 18 log-points for high-school graduates

[1] We trim the top and the bottom (which include 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.

and 7 log-points for college graduates during the first year in the labor market. Fifteen years after labor market entry, the gaps increase to 28 and 32 log-points for high school and college groups respectively.

In order to investigate the factors contributing to the gender wage gap and its expansion over the life-cycle, we first decompose the gap empirically by sequentially controlling for more variables. Figure 2 shows the log hourly wage gap between men and women by potential experience, (i) unadjusted, (ii) after adjusting for actual experience, and (iii) after adjusting for occupations and industries in addition to actual experience.

Figure 2: *Gender Wage Gap over the Life-Cycle*



Notes: The lines in the figures above represent the coefficients of the male dummy in each month of potential experience in the following regressions: (i) unconditional; (ii) adding a quadratic in actual experience as control; and (iii) adding 3-digit occupation and industry fixed effects in addition to (ii). All the regressions control for year fixed effects. The shaded areas corresponds to their corresponding 95% confidence interval.

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. But even later in the life-cycle, actual experience accounts for only a small proportion of the wage gap. Occupation and industry fixed effects account for a greater portion of the gender wage gap especially for the college group, suggesting occupational sorting by gender in both early and late careers.

However, there is still a substantial "unexplained" gap of 17 and 9 log-points on average for high school and college graduates respectively. This suggests that similarly qualified men and women receive unequal pay for doing similar jobs, potentially due to firms' wage-setting decisions as we explore more in Section 3.

2.2 Gender differences in turnover

The regressions in the previous section Section 2.1 controlled 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 actual experiences, but might also impact firms' expectations about workers' behaviors. Therefore, these differences may impact firms' equilibrium wage-setting and thus account for at least some part of the residual gap in Figure 2. In Section 2.2, we document these gender differences in labor market behaviors in our sample. In Section 3, we lay out our model linking these differences with firms' wage-setting policies in equilibrium.

Table 1 presents several aspects of gender differences related to labor market turnover and fertility interruptions that emerge in the first 15 years of the life-cycle. High school and college men work 11.7 and 12.8 years out of 15, but high school and college women work 1.5 and 1.1 years less than their male counterparts. We treat the states of unemployment and out-of-the-labor force as the same non-employment state throughout the paper. 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 19% lower than men's. For the college group, the separation rate of women is a striking 58% higher than that of men, potentially driven by family responsibilities. Note that these transition rates are all computed outside of fertility events, which we discuss below.

In order to examine fertility-related career interruptions, we use the information in NLSY79 on the timing of childbirth. Although we do not directly observe parental leave or job protection in the data, we can infer child-related non-employment from the worker's employment history. We assume that a worker is in *parental leave* (PL) if he/she is non-employed in any of the first 20 weeks of the child's life. If a worker was not working in the weeks preceding childbirth, these weeks are counted as parental leave for up to 3 months before the date of birth. Parental leave lasts until the worker is observed working for at least 4 consecutive weeks. We infer that the leave is *job-protected* by the employer if the worker goes back to the same job when parental leave ends.

In our sample, women have slightly higher fertility rates than men. However, women stay in parental leave for a much longer period than men for each child. According to our definitions, women spend about 2 months in job-protected parental leave whereas men spend only a week. Those who did not enjoy job protection spend a much longer time at home with the baby — high school and college women spend 17 and 15 months in parental leave if they do not go back to the same employer, and men in the same situation spend about 4 months. Although most of the childbirths in our sample happened before job protection was mandated by the Family and Medical

Table 1: *Summary Statistics by Gender and Education*

	High School		College Graduate +	
	Men	*Women*	*Men*	*Women*
Sample Size	1376	1331	653	681
Actual experience (years)	11.6891	10.1749	12.8230	11.7318
	(0.0984)	(0.1116)	(0.1302)	(0.1399)
Number of children	1.1940	1.4891	1.2757	1.3715
	(0.0306)	(0.0322)	(0.0485)	(0.0465)
Same job after PL	0.897	0.6943	0.9541	0.8058
Time spent in PL (months)				
Same job after PL	0.3151	1.9686	0.1449	1.8423
	(0.0337)	(0.1026)	(0.0081)	(0.2236)
Different job after PL	4.4867	16.9850	3.6523	14.8117
	(0.4876)	(1.0669)	(0.7253)	(2.0007)
Transition rates outside PL				
Job-finding rate	0.2217	0.1681	0.2198	0.1977
Separation rate	0.0340	0.0367	0.0155	0.0245
Job-to-Job transitions	0.0201	0.0162	0.0156	0.0168

Notes: This table reports the differences in turnover rates across genders by the time that workers have been in the labor market for 15 years according to the NLSY79.

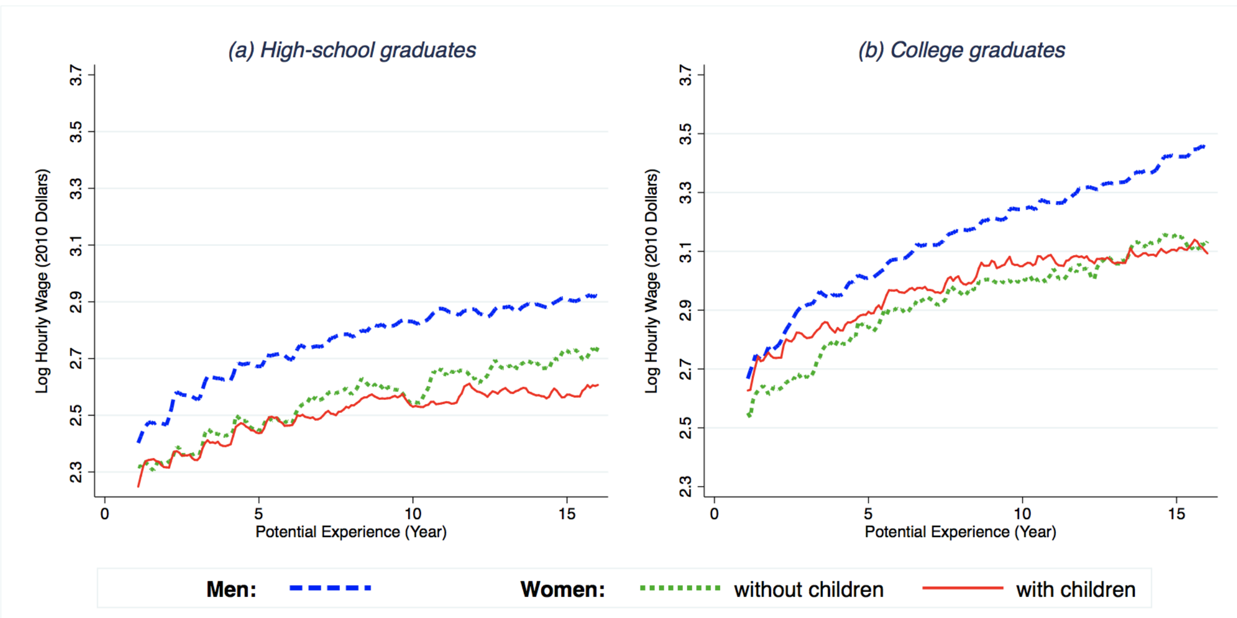
Leave Act (FMLA) in 1993, it seems that many firms voluntarily offered job protection to women. 70% of high school women and 81% of college women were able to go back to the same employers after having children. Job protection rates are much higher for men (90% and 95% for high school and college men), presumably because they go back to work soon after childbirth. These gender differences in job protection and parental leave duration are incorporated into our model.

In our sample, 26% of high-school graduate and 34% of college graduate women never had any child during the entire sample period, and these women behave more similar to men in terms of labor force attachment (see Figure 9 in Appendix A). If employers could perfectly predict workers' labor market behaviors and fertility patterns, then they would remunerate childless women in a similar way as they would reward men. However, if individual transition rates and fertility interruptions are difficult to foresee, then employers might use gender (and education) to predict the average behavior of the group. That is, if employers anticipate women to be much more affected by childbirth than men, and if these child-related interruptions are costly for firms, then we might expect employers to incorporate some of these costs into wage offers and statistically discriminate against women.

Figure 3 provides suggestive evidence that statistical discrimination might be indeed at play. For the high school group, although childless women have the same employment patterns as men (see Figure 9 in Appendix A), 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 also 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 relative to women with children. Childless women also have lower wages than women with children, possibly because of negative selection (Calvo et al. (2020)). Nevertheless, over the course of their careers, childless women accumulate more experience and their wages grow more over time than women with children.

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



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

3 Model

Time is continuous and we focus on the steady-state analysis. Male and female workers are each composed by two (exogenously determined) education groups representing high school graduates and college graduates. Each gender-education group is a separate labor market, so that the parameters governing firm productivities, human capital accumulation technology, fertility process and labor market turnover are all assumed to be gender and education specific. In what follows, we describe workers' and firms' problems in one of the four labor markets. All gender $g \in \{m, f\}$ and skill superscripts $s \in \{\text{Highschool}, \text{ College}\}$ are omitted to keep the notation as simple as possible.

In this section, we use the "she/her/hers" pronouns to refer to a generic worker in the framework, however the structure of the model is entirely synonymous for men as well.

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

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

Firms are risk-neutral and operate according to a constant returns to scale technology. They are heterogeneous in productivity, p, drawn from an exogenous distribution $\Gamma(p)$ with support $\left[\underline{p}, \overline{p}\right]$.[2] Every firm posts a wage offer consisting of a single wage rate z to all potential applicants, employed and unemployed. If a worker with productivity y accepts this offer, she matches with the firm, she gets paid a wage $w = zy$, reflecting the initial ability of the worker, her actual experience which increases her productivity at rate ρ, and the wage rate z that the firm posts to maximize its steady-state expected profits. The flow productivity of the match (y, p) is yp, so that the firm's flow profit from the match (y, p) is $(p - z)y$. Thus, each firm p chooses an offer z to maximize its aggregated expected steady state profits $\pi(p, z)$ from all the matches that will be formed.[3]

Let $F(z)$ denote the wage offer distribution, the fraction of the firms that offer wage rates no greater than z. This offer distribution is determined in equilibrium through firms' optimal choice of z.[4]

Workers can receive job offers both in unemployment 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 firm may end for a number of reasons: first, a worker might be poached by some firm offering a higher wage rate z'; second, workers face the risk of separation into unemployment 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 (or *PL*).

Transitions into and out of *PL* are as follows. Workers may have a child in either employment or unemployment according to a Poisson process with rate γ_1. If the worker was employed

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

[3] Informational frictions give monopsony power to firms, that choose to pay less that the marginal productivity. In particular, they pay $w = zy$ where z is a fraction of p, say θ. I.e. $w = \theta py$.

[4] In equilibrium, the distribution F has a bounded support and no mass points.

when he/she has a child, he/she separates from the current job to take parental leave, and his/her employer decides whether to provide him/her with job protection. We model this decision in a reduced-form and parsimonious way by assuming that there is a chance η that a job will be kept for a worker while he/she is on leave, and a chance $1-\eta$ that he/she will lose her job and will have to start searching again when she comes back to the labor market from parental leave. If he/she receives job protection, he/she enters parental leave with job protection and we call this state *JP*. In this case, they stay in state *JP* until their spell at home with the baby ends, and this spell ends according to another Poisson process, with rate γ_2. If the worker does not receive job protection (with probability $1-\eta$) or if the worker is unemployed, then the worker enters the "no job protection" state *NJP*, which is an unprotected parental leave state and does not allow him/her to go back to her previous employment when the spell at home with the baby ends. The spell ends following a different Poisson process γ_3. If the worker has a second child while in the state *JP*, he/she losses the job protection provision and goes into the state *NJP*. So at each point in time, the worker is either employed, unemployed, in *JP* or *NJP* for as long he/she is in the labor market.

3.1 Workers' Behavior

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

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

$$(r+\phi)U(y) = by + \lambda_u \int \max\left\{0, V(y,z') - U(y)\right\} dF(z') + \gamma_1 \left(W^{NJP}(y) - U(y)\right). \tag{1}$$

The flow payoff of the worker is by, which reflects her value of leisure or home production. She gets a job offer (that is, sees the vacancy posted by a firm which consists of a wage rate offer z') at rate λ_u, and accepts it if the maximum expected lifetime payoff taking the job is higher than her current value of unemployment $U(y)$. At rate γ_1, the worker will have a child and, since she is not eligible for job protection, she enters *NJP*, stops sampling from F and enjoys $W^{NJP}(y)$, which denotes the value of staying at home with the baby with no job protection.

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

$$
\begin{aligned}
(r+\phi)V(y,z) = zy + \rho y \frac{\partial V(y,z)}{\partial y} + \lambda_e \int \max\left\{0, V(y,z') - V(y,z)\right\} dF(z') \\
+ \gamma_1 \big(\eta W^{JP}(y,z) + (1-\eta) W^{NJP}(y) - V(y,z)\big) + \delta\big(U(y) - V(y,z)\big). \qquad (2)
\end{aligned}
$$

The worker enjoys a flow payoff that is her wage zy. The value of employment grows due to human capital accumulation, by the amount $\rho y \partial V(y,z)/\partial y$. There is on-the-job search, so the worker receives job offers at rate λ_e and moves to a new firm offering wage rate z' if $V(y,z) < V(y,z')$. Since human capital is both general and transferable across firms, the worker moves to any outside offer z' that is greater than the current wage rate. At rate γ_1 she has a child and with probability η she enter the job-protected parental leave state *JP*. With the complementary probability, $1-\eta$, the firm does not provide job-protection and she enters *NJP*.

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

$$
(r+\phi)W^{JP}(y,z) = b^{out}y + \gamma_2\big(V(y,z) - W^{JP}(y,z)\big) + \gamma_1\big(W^{NJP}(y) - W^{JP}(y,z)\big). \qquad (3)
$$

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

Finally, let us consider a worker in unprotected parental leave, with value $W^{NJP}(y)$ given by

$$
(r+\phi)W^{NJP}(y) = b^{out}y + \gamma_3\left(U(y) - W^{NJP}(y)\right). \qquad (4)
$$

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

As we show in Appendix B.1, the value functions take the following separable form,

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

$$W^{NJP}(y) = \alpha^{NJP} y.$$

where α^U and α^{NJP} are scalars and $\alpha^E(z)$, $\alpha^{JP}(z)$ are some (yet unknown) functions of z.

To simplify notation, let us denote the total quit rate by $q(z)$ as follows

$$q(z) = \phi + \delta + \gamma_1 + \lambda_e \overline{F}(z), \tag{5}$$

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

Proposition 1. *For a given offer distribution $F(\cdot)$ with bounded and non-negative support, optimal job search implies that*

(i) $\alpha^E(z)$ is the solution to the differential equation $\frac{d\alpha^E(z)}{dz} = \frac{1}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}$.[5]

(ii) The tuple $\left(\alpha^{NJP}, \alpha^{JP}(z), \alpha^U, z^R\right)$, satisfies the following four equations,

$$\begin{aligned}
&\alpha^{NJP} = \frac{b^{out} + \gamma_3 \alpha^U}{r+\phi+\gamma_3}, \\
&\alpha^{JP}(z) = \frac{b^{out} + \gamma_2 \alpha^E(z) + \gamma_1 \alpha^{NJP}}{r+\phi+\gamma_1+\gamma_2}, \\
&\left[\zeta_1(\lambda_u - \lambda_e) - \rho\lambda_u + (r+\phi)\zeta_2\right]\alpha^U = \lambda_u z^R - \lambda_e b + \left[\zeta_2 + \frac{\gamma_1(\lambda_u - \lambda_e)}{r+\phi+\gamma_3}\right] b^{out}, \\
&\zeta_1 \alpha^U = b + \frac{\gamma_1}{r+\phi+\gamma_3} b^{out} + \lambda_u \int_{z^R}^{\overline{z}} \frac{\overline{F}(z)}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma 2}}\, dz,
\end{aligned}$$

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

(iii) Using the above four equations, the reservation wage z^R is implicitly defined by

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

[5]The boundary condition is

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

and given the boundary condition, the solution is unique.

3.2 Steady State Flow Conditions

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

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

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

3.3 Firms' Profits

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

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

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

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

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

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

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

$$y^{acc}(z) = \int_{\tau=0}^{\infty} \left[q(z) e^{-q(z)\tau} \int_0^\tau e^{\rho x} dx + \eta \gamma_1 e^{-q(z)\tau} e^{\rho\tau} \int_{\ell=0}^{\infty} \gamma_2 e^{-(\phi+\gamma_1+\gamma_2)\ell} y^{acc}(z)\, d\ell \right] d\tau. \tag{6}$$

Note that $y^{acc}(z)$ consists of two parts. The first part is the expected accumulation that happens over the duration of the match before any separation takes place — this separation can be due to retirement ϕ, exogenous destruction shocks δ, a transition to a better job $\lambda_e \overline{F}(z)$ or a child shock γ_1 — all elements of $q(z)$ (see equation (5). The second part of $y^{acc}(z)$ is relevant only in the case where the worker gets job protection when having a child and she returns to her previous employer after parental leave. The probability that she receives job protection upon a child shock after a match of length τ is $\eta \gamma_1 e^{-q(z)\tau}$. To ensure that she returns to the previous job, the event of returning to work should occur before retirement or an additional fertility shock — this happens with probability $\gamma_2 e^{-(\phi+\gamma_1+\gamma_2)\ell}$ for any duration of parental leave ℓ.

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

Simplifying equation (6), the firm's problem becomes,

$$\max_z \quad \frac{(p-z)\widetilde{\varepsilon}}{q(z) - \rho - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}} \left(m_U \lambda_u \int_0^\infty e^{\rho x'} dN(x') + m_E \lambda_e \int_{z^R}^{z} \int_0^\infty e^{\rho x'} d^2 H(x', z') \right). \tag{7}$$

We denote the optimal wage rate offer function by $z = \xi(p)$. We solve for the equilibrium in Appendix B.4 and show that the optimal policy function has the recursive form given in Proposition 2 below.

Proposition 2. *The optimal policy function, $z = \xi(p)$,* *i) can be expressed as*

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

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

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

3.4 Definition of Market Equilibrium

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

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

ii) Workers' behaviors are optimal and z^R satisfies equation (Proposition 1).

iii) For any $p \in [\underline{p}, \overline{p}]$, the firm's optimal offer $z = \xi(p)$ maximizes expected profits and satisfies (26).

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

We consider the reference time period as a month, and fix the following parameters. The retirement rate ϕ is fixed at 0.0033 so that workers have an average of 25 years of prime-age career. We assume a monthly discount factor $r = 0.0041$ following the literature (Hornstein et al. (2011)). There are thus 14 parameters to estimate for each gender and education group — ρ, $\underline{p}$, $\overline{p}$, κ_1, κ_2, α_1, α_2, b, δ, γ_1, γ_2, γ_3, λ_e and λ_u.

Out of the above 14 parameters, 6 have direct data counterparts. We derive closed form expressions for fertility and turnover moments in the data as functions of the Poisson rates δ, γ_1, γ_2, γ_3, λ_e, λ_u, independent of the other eight model parameters. Notably, although the job-to-job transition rate of someone receiving wage rate z is endogenous and depends on both 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 job-to-job transitions 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 C.1.

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

Given the specification outlined above, all parameters in β are jointly identified by all targeted moments. We provide an intuition for identification in several steps. First, since human capital is general and remains the same when carried over to a new job, the wage change during a job-to-job transition is only related to the changes in human capital prices (the z's) offered in different firms. Therefore, 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 $F(z)$. The one-to-one relationship between wage offer z and firm productivity p derived from the model will then help to identify the shape parameters of $\Gamma(p)$. Second, recall that wage growth in the model can come either from wage upgrades during job-to-job transitions or from human capital accumulation within each job spell. Given that the frequency and amount of wage change due to job-to-job moves are pinned down in the first step, the rest of the wage growth in the population informs us about the human capital accumulation rate ρ. Third, we fix the reservation wage in the model to be equal to the lowest wage observed in the data, which helps to identify the lower bound $\underline{p}$ in the support of $\Gamma(p)$. The reservation wage rate is a function of ρ and b. The efficiency rate in unemployment b

is fixed to the empirical replacement rate in unemployment for our sample period, as reported in Van Vliet and Caminada (2012).[6] Fourth, any discrepancy in the wage level, dispersion, skewness and kurtosis between the data and the model that are not captured by $F(z)$ or ρ would inform the distribution of initial productivities $A(\varepsilon)$.

To sum up, our target moments are the first four moments of the log-wage distribution (mean, variance, skewness and kurtosis) together with the average wage change at job-to-job moves, evaluated at actual experience years from 1 to 10. These add up to 50 moments in total for each gender-education group.

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

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

where we set the matrix W to be the inverse of the diagonal variance-covariance matrix of the data moments rather than the optimal full variance-covariance matrix, due to 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 job-finding rates are lower than men's, and the difference is more pronounced for the high school group. Men's Poisson exit rates out of parental leave is 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 C.2.

The estimates of the human capital accumulation rate show that college men have a much higher ρ than college women, but high school men and women have very similar accumulation rates. The sizable gender gap in ρ for the college group is potentially driven by the nature of the jobs in the high-skill sector, which might entail substantial learning on the job and within-job

[6]As documented in Table 3 of Van Vliet and Caminada (2012), the mode of the net unemployment replacement rate is 0.58 over our sample period 1978-2005

Table 2: Turnover parameters

		High School		College	
		Men	*Women*	*Men*	*Women*
Separation rate	δ	0.035	0.038	0.016	0.025
Job-finding rate	λ_u	0.252	0.185	0.258	0.222
JTJ transition	λ_e	0.044	0.035	0.034	0.036
Fertility rate	γ_1	0.710×10^{-2}	0.762×10^{-2}	0.663×10^{-2}	0.827×10^{-2}
Exit rate out of Job-protected PL	γ_2	3.164	0.496	6.892	0.532
Exit rate out of PL without JP	γ_3	0.121	0.072	0.305	0.013
Job protection rate	η	0.900	0.711	0.956	0.822

Notes: This table reports the values of our calibrated parameters.

wage growth. These high-end jobs might disproportionately reward long work hours (as in Goldin (2014)) and provide high returns to job training. These opportunities of wage growth might be more easily available to men.

As would be expected, the support of the firm productivity distribution for men is shifted to the right compared to women's for both education groups. The shape parameters for workers' initial productivity distributions imply that the mean initial log-productivity is almost twice as high in the high-skill market than in the low-skill market. The gender differences within skill groups are moderate — about 4 log-points to the favor of men in low-skill group, and about 3 log-points to the favor of women in high-skill group. We interpret these gender differences in initial productivities as residual gap, 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, as well as taste-based discrimination (in the labor market or during schooling years).

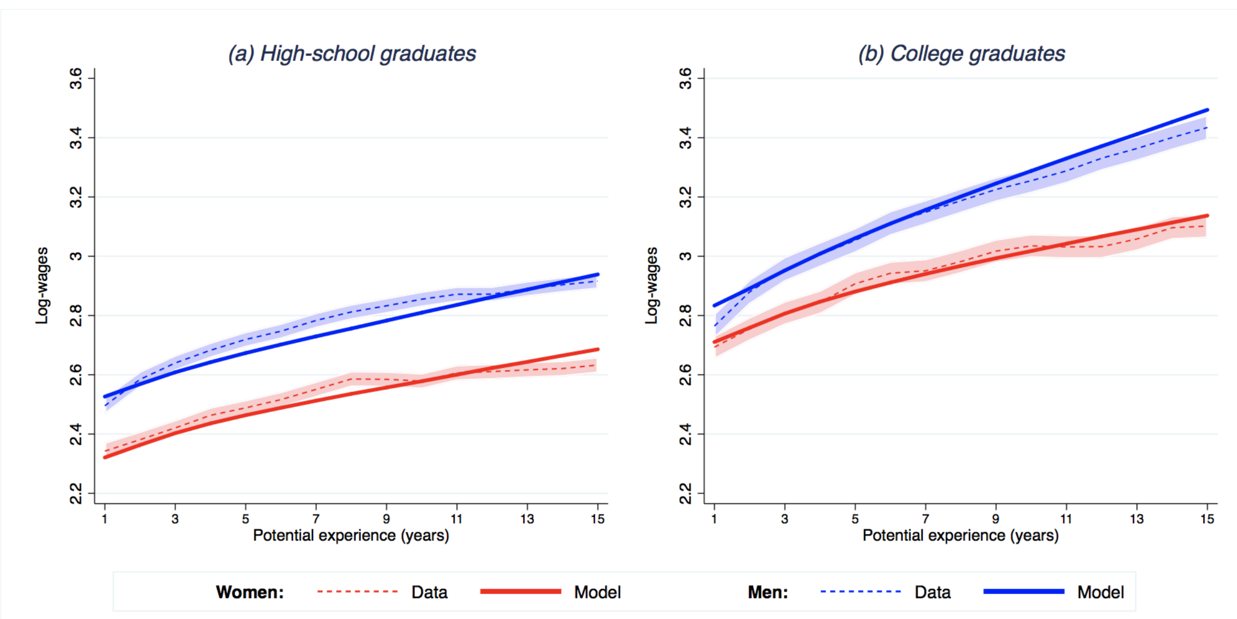
We show the model fit for all targeted moments in Figure 10 and Figure 11 in Appendix D. Although we do not target average wages by potential experience, Figure 4 shows that our parameter estimates perform very well in fitting the untargeted moments — log-wage profiles by *potential* experience. Note that these wage profiles combine (i) the wage growth by *actual* experience, targeted in the GMM estimation, and (ii) the realization of *actual* experience over potential experience, as implied by transition parameters calibrated separately based on turnover data. So Figure 4 shows the fit between model and data for both the jointly estimated parameters and the exogenous transition rates.

Table 3: *Jointly estimated parameters*

		High School		College	
		Men	*Women*	*Men*	*Women*
$\boldsymbol{\rho}$		2.493×10^{-3}	2.503×10^{-3}	3.504×10^{-3}	2.445×10^{-3}
		(0.000)	(0.000)	(0.000)	(0.000)
$\boldsymbol{\Gamma}(p)$	$\underline{p}$	6.648	4.938	6.242	4.961
		(0.080)	(0.002)	(0.112)	(0.050)
	$\overline{p}$	24.358	13.993	27.347	17.321
		(1.096)	(0.006)	(2.287)	(0.693)
	k_1	0.626	1.564	0.246	0.624
		(0.025)	(0.006)	(0.008)	(0.024)
	k_2	13.183	96.325	99.999	13.010
		(0.751)	(0.106)	(4.613)	(0.677)
$\boldsymbol{A}(\varepsilon)$	α_1	1.065	1.121	1.650	1.968
		(0.039)	(0.002)	(0.128)	(0.058)
	α_2	0.640	0.563	1.658	1.716
		(0.022)	(0.001)	(0.034)	(0.038)
$\boldsymbol{b}$		5.212	4.217	4.723	3.961
		(0.122)	(0.003)	(0.107)	(0.105)

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

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



Notes: The figures show the fit of the model by number of years in the labor market—this corresponds to the joint fit of the parameters estimated via GMM (see Table 3) together with the calibrated parameters (see Table 2). The solid lines represent the log-wages as predicted by the model, while the dashed lines represent the equivalent data moments. The shaded areas correspond to a point-wise 95% confidence interval.

5 Counterfactual Analyses

5.1 Decomposing the life-cycle gender wage gap

Based on the estimates of the structural parameters, we use the model to analyze the drivers of the life-cycle gender wage gap. First, we decompose the gender wage gap into several additive parts. For clarity, we add the gender superscripts but fix the education group $s \in \{\text{Highschool, College}\}$ and omit the education superscript to keep the notation as simple as possible. Let us denote with $w^g = y^g z^g$ the wages received by workers of gender $g \in \{f, m\}$. We can decompose the expected gender wage gap, denoted by $\overline{gap}$, as

$$\begin{aligned} \overline{gap} &= \overline{\log(w^m)} - \overline{\log(w^f)} \\ &= \underbrace{\overline{\log(y^m)} - \overline{\log(y^f)}}_{\text{gap in HC levels}} + \underbrace{\overline{\log(z^m)} - \overline{\log(z^f)}}_{\text{gap in HC prices}} \end{aligned} \tag{8}$$

Note that the second term in equation (8), the gap in human capital prices, can be driven by three factors: first, men and women are in different firms because some firms do not employ women and and some firms do not employ men; second, men and women are in different firms because women might not advance on the job ladder as fast as men; and third, men and women in the same firm are 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 firms 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 and fertility-related interruptions.[7]

Using the above notation, we denote $\overline{\log(z)}\ |_{\Lambda, F(\Omega,\Theta)}$ as the average counterfactual wage rate at a given point in life. 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. Therefore, $\overline{\log(z)}\ |_{\Lambda^m, F(\Omega^f, \Theta^m)}$ denotes the counterfactual average wage that men would receive when they face the firms 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 (8)

[7] 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 due to 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).

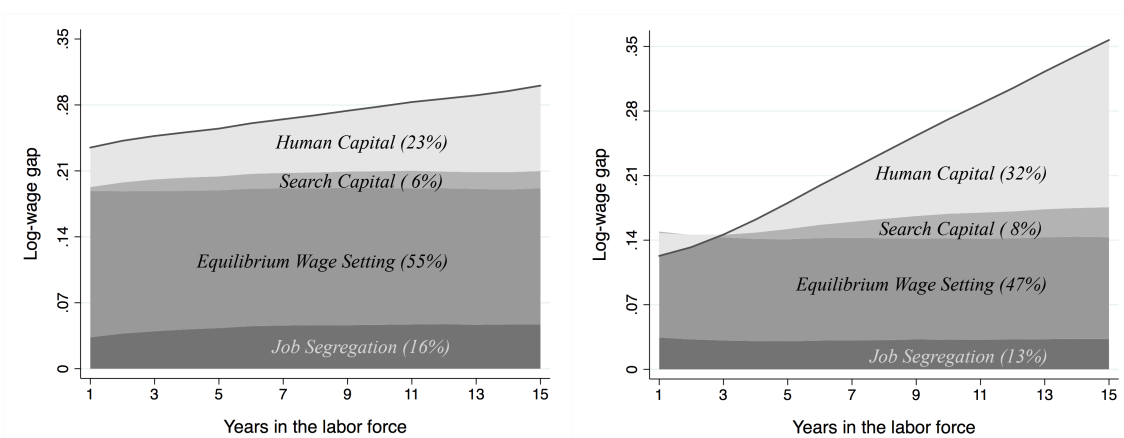
can be further decomposed as

$$\overline{\text{gap}} = \overbrace{\overline{\log(y^m)} - \overline{\log(y^f)}}^{\textit{gap in HC levels}} + \overbrace{\overline{\log(z)}\,|_{\Lambda^m, F(\Omega^m, \Theta^m)} - \overline{\log(z)}\,|_{\Lambda^m, F(\Omega^f, \Theta^m)}}^{\textit{job segregation}} \tag{9}$$
$$+ \underbrace{\overline{\log(z)}\,|_{\Lambda^m, F(\Omega^f, \Theta^m)} - \overline{\log(z)}\,|_{\Lambda^f, F(\Omega^f, \Theta^m)}}_{\textit{search capital}} + \underbrace{\overline{\log(z)}\,|_{\Lambda^f, F(\Omega^f, \Theta^m)} - \overline{\log(z)}\,|_{\Lambda^f, F(\Omega^f, \Theta^f)}}_{\textit{equilibrium wage setting}}.$$

Equation (9) decomposes the gender wage gap at any given point of the life-cycle into the following four additive channels: *i)* the *human capital channel* captures the difference in wages because men tend to work more months of the year and accumulate more experience than women; *ii)* the *jobs segregation channel* captures the change in mean $log(z)$ when Ω_f is changed to Ω_m, reflecting the different productivities in the jobs employing men compared to those employing women; *iii)* the *search capital channel* emerges when Λ_f changes to Λ_m, capturing the fact that women's turnover patterns make them progress up the ladder at a different pace than men; and *iv)* the *equilibrium wage setting channel* reflects the change in offer distribution $F(\cdot)$ when Θ_f changes to Θ_m, measuring the difference in the prices per unit of human capital that men and women would be offered in the same job.

Figure 5: *Decomposition of the gender wage gap over the lifecycle*

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



Notes: The figure shows the total log-wage gap (black solid line) and its components: the gap due to human capital differences (top light gray area) and the gap in the prices that men and women get for their human capital which corresponds to the bottom three areas: the gap in search capital (second area), the gap in equilibrium wage setting (third area) and the gap due to segregation (bottom dark gray area). In parentheses we show the percentage contribution of each of these regions averaged over the life-cycle.

Figure 5 illustrates the relative importance of these four components over the life-cycle. The solid black line represents the total gender wage gap, and the gray areas represent the four additive components outlined in equation (9).

For both education groups, most of the total wage gap can be attributed to firms' differential wage-setting towards men and women; this equilibrium channel explains, on average, 55% and 47% 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 in late career. Firms that employ men and women come from different parts of the productivity distribution, but the role of this job segregation channel is relatively small for both education groups. The search capital channel also plays a small role, potentially because the transition events are rare. Once the ladder for each gender is set, the differential speed in climbing it does not substantially affect the gender wage gap.

It is worth noting that the wage dynamics over the lifecycle 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. Since firms' wage-setting channel remains quite stable over the lifecycle, most of the expansion in the gender wage gap is driven by the human capital channel. Human capital is a major factor of the college wage gap later in the lifecycle, because men face a much higher return to experience than women in the high-skill labor market, whereas the returns are very similar across genders in the low-skill market. We discuss this channel more in Section 5.3.

Since employers' differential wage-setting is a major source of the gender wage gap for both skill groups, 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.

5.2 Steady-state wage-setting by firms

Our model sheds light on the mechanisms behind firms' wage-setting process. Firms choose profit-maximizing wage rates taking into account gender differences in human capital dynamics, mobility patterns and fertility-related career interruptions. Thus, the gender gap in offered wage rates is a measure of firms' differential treatment towards otherwise comparable men and women. Decomposing the sources of this portion of the gender wage gap is of particular interest to us, because this is typically regarded as part of the "unexplained gap" in the literature. Moreover, understanding employers' wage-setting rules is crucial for policy-making, because policies aimed to help workers would be misguided if they neglect equilibrium responses of firms.

In the section below, we illustrate the differences in wage offer distributions faced by men and women given the parameter estimates from Section 4.2.

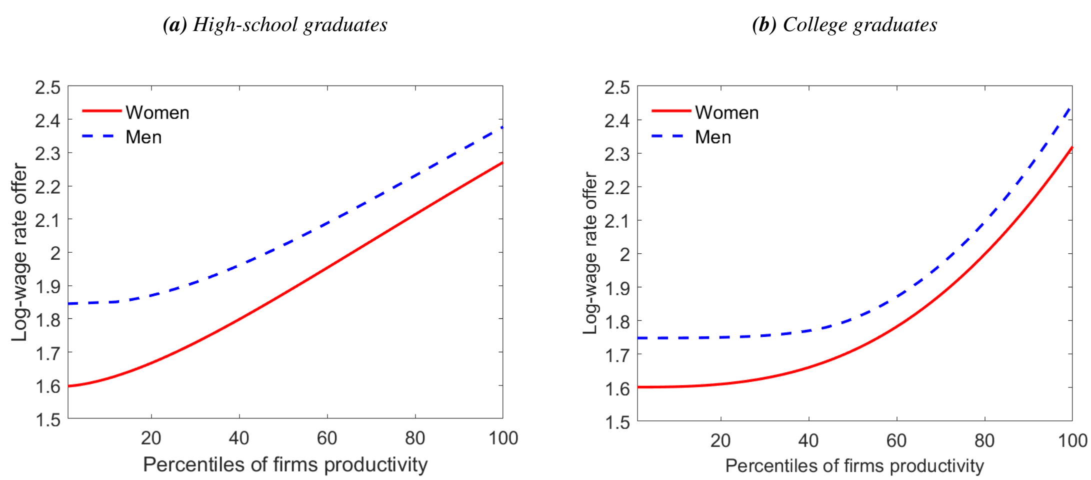
5.2.1 Gender differences in wage offer distributions

In each labor sub-market, a firm of a given productivity p chooses a profit-maximizing wage rate z according to Proposition 2 in Section 3. Each gender-specific parameter can influence this wage-setting process in different ways, and the size of the response can be different for a high- versus low-productivity firm for a given parameter change.

Figure 6 shows the equilibrium wage rates that would be offered to men and women for each job productivity percentile, for high school and college groups respectively. We obtain counterfactual male wage rates by computing the equilibrium wage function (Proposition 2) using estimates for men in human capital, transitions and fertility parameters.

In both low- and high-skilled labor markets, employers implement different wage policies towards men and women. On average, log-wage rate offers are 16 and 13 log-points higher for men than for women in high school and college educated populations, respectively. There is also considerable variation in the size of these gender gaps across the firm productivity distribution. For high school graduates, the gender gap in offered wages is much more pronounced in low-productivity jobs than in high-end jobs — the gap is 25 log-points in the bottom firms, compared to 11 log-points in top firms. For the college group, the gender gap in offered wages is similar in low- and high- productivity firms — 15 and 13 log points, respectively.

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



Notes: The red solid lines show the equilibrium wage rates for women as implied by the parameter estimates. The blue dotted lines show the counterfactual wage rates of men when facing the same firms that employ women.

Keep in mind that even though search is random in our model, over time workers do move on to firms higher and higher up on the job ladder through on-the-job search. Therefore, understanding how high- and low-end firms design their wage policies informs us about the relative importance of the equilibrium wage-setting channel at different points in the life-cycle.

The overall gender gap in offer distributions is driven by the wage rate each gender draws from the steady-state offer distributions, as well as the amount of human capital they have accumulated up to that point in their career. Each dimension of workers' attributes contributes to both of these. In Section 5.2.2 we discuss the mechanisms that translate workers' attributes into differential wage offers by gender within the same firm, that is we investigate how each of the gender differences affects the gender gap in wage offers shown in Figure 6. Then, in Section 5.3 we discuss and compare the contributions of different parameters to the life-cycle gap taking into account their full impact on wage profiles — including differential wage offers discussed in Section 5.2.2, — as well as the speed with which men and women advance through the firm hierarchies and the amount of time they spend working and learning on-the-job.

5.2.2 Mechanisms of wage-setting policies

What role do specific parameters play in the above gender gaps in offered wages, and what are the mechanisms behind firms' differential wage-setting policies?

In Figure 7, we decompose the overall gender gap in log-wage offers (depicted in Figure 6) into portions explained by specific parameters. Each bar in Figure 7 represents the log-wage gap generated by the gender difference in a given parameter, at a fixed percentile of women's jobs productivities.

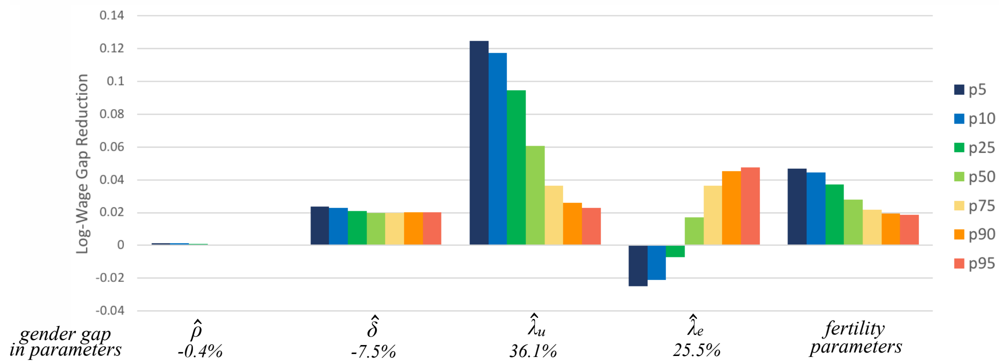
Recall that the gender-specific parameters that affect equilibrium wages include: separation rate δ, job-finding rate λ_u, job-to-job transition rate λ_e, human capital accumulation rate ρ, non-work income replacement rate b, and fertility parameters including fertility rate γ_1, parental leave durations γ_2 and γ_3 and job protection rate η. Bars with a positive height associated with a parameter show the amount that the wage gap would *shrink* when we equalize the parameter across genders; conversely, bars with a negative height imply that the wage gap would *widen* if women had the same parameter value as men. For example, Figure 7(a) shows that the job-finding rate λ_u of high school men is estimated to be 27% higher than that of high school women. If we were to eliminate the gender difference in λ_u for high school graduates, a low-end firm would raise women's wage rates by 13 log-points and a median firm would raise it by 6 log-points and so on.

It is easy to see that different forces are at play for different education groups. For example, the job-finding rate λ_u is a major source of the high school equilibrium wage gap, whereas it does not play a big role for the college group. While the gender differences in separation rate δ and human capital growth rate ρ are small for the high school group, they are sizable for the college group and have considerable impacts on the offered wage rates of college graduates.

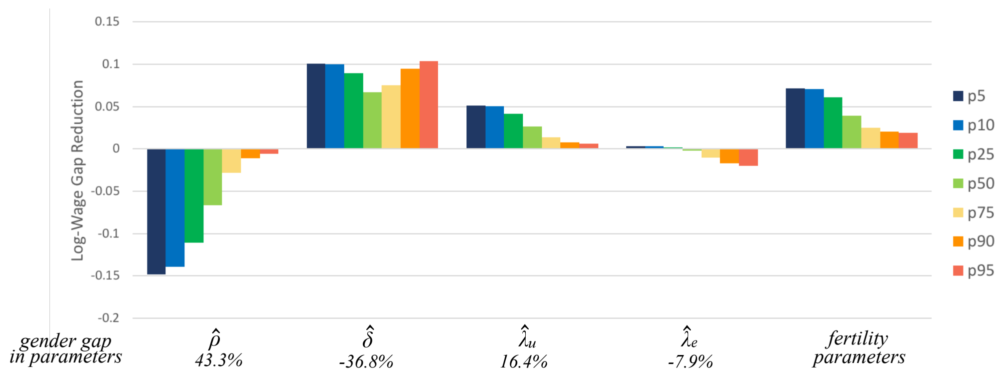
In order to understand the equilibrium impact of each parameter on the gender gap in offered wage rates, it is important to recognize the firms' considerations in profit maximization. Note that whenever a worker characteristic — for example, low separation rate, — implies higher expected

Figure 7: *Components of the gender gap in offered wage rates, by percentiles of firm productivity*

(a) *High-School graduates*



(b) *College graduates*



Notes: The figure shows the share of the total improvement in offers at different percentiles of the firms distribution, accounted for by a change in a specific parameter. The top panel displays the improvements in offers corresponding to the high school group and the bottom panel the ones corresponding to the college group.

match profits, the forces of competition will make the firm actually increase its offer. Therefore, in equilibrium firms reward worker attributes that imply higher expected profits.

Note also that the above considerations operate differently for firms of different productivity levels. Low-productivity firms hire almost entirely from the pool of the unemployed, who are ready to work for any wage rate above the reservation rate. Therefore, expected profits of such firms are especially sensitive to the characteristics of the unemployed. In contrast, the firms higher up the ladder engage in poaching and a substantial share of their new hires comes from other firms.[8] Therefore, high-productivity firms will put significant weight on the characteristics of the employed workers and on the degree of the competition between the firms. Furthermore, top firms will also be more sensitive to the parameters affecting expected match duration, since they lose disproportionately more flow output when the match dissolves. Though search is random in our

[8] For example, for a top-productivity firm in the high-skill market, poached workers make up over a half of its total new-hires inflow as implied by our model.

model, there is positive assortative matching between firms and worker types in equilibrium. This is because it takes time to reach top firms through on-the-job search, and workers accumulate human capital throughout the employed periods. Therefore, more productive firms enjoy a more experienced workforce in steady-state equilibrium. Since the productivities of the firm and the worker are complements in production (py), top firms will have more incentives to bid up offers to attract and retain their workers.

Finally, since firms of all productivity levels compete in the same market and take into account each other's wage-setting strategies, there are also spillover effects, where, for example, an increase in the offers of high-productivity firms will induce low-productivity firms to raise their rates as well in order to retain their workforce. We explain the model mechanisms of each parameter below.

Separation rate δ

As Figure 7 shows, the gender difference in separation rates is especially important for the wage gap at the extremes of the productivity range (this effect is less pronounced for the high-school group). The intuition is the following. Low-end firms raise their offers in response to the human capital of the unemployed, which is significantly higher under a low separation rate.

At the high-end, firms both enjoy an especially high flow output and also face a tighter competition for workers, since matches last longer and the risk that a worker will be poached is higher. These two forces make high-end firms generously reward a group with low separation rate — in our framework, it is men. In other words, women's higher separation rates give rise to a glass ceiling effect in the menu of offers. This is evident especially for the college group, where the gender difference in δ of 58% explains almost the entire gap in wage offers at top jobs. In the mid-range of productivities, firms raise their offers by less than at the extremes — because on the one hand, they do not value a better composition of the unemployed population to the same extent as firms at the low end, and on the other hand, they do not value match stability to the same extent as highly productive firms.

For high school graduates, men's separation rate is only 9% lower than that of women, and δ plays a small role in the gender gap in equilibrium offers.

Job-finding rate λ_u

In general, employers offer a higher wage rate to the group of workers with a higher job-finding rate. Men's higher job-finding rate in unemployment has two implications: first, since unemployed women do not encounter job opportunities as often as men, they lower their expectations and accept lower wages; and second, it implies men have shorter unemployment spells and accumulate more human capital on average. From the employer's point of view, the gender difference in job-finding rates implies that the firm encounters and hires a fewer of unemployed women than men per unit of time, and thus earns less profit from women. As a result, a given firm will offer a higher wage rate to men than women both because men's reservation rate is higher, and because the firm passes some of the higher profit margin into men's wages due to competition.

These considerations are especially important for the firms at the bottom of the productivity distribution who hire mostly from the pool of the unemployed. For high school graduates, Figure 7(a) shows that men's λ_u is 27% higher than women's, and this leads to a male wage offer that is 13 log-points higher in low-end jobs and only 2 log-points higher at top jobs. The low job-finding rate of high school women is a major source of the gender gap in offered wages, especially in low-productivity jobs. Policies that help high school women with efficient job search in unemployment would thus improve their wage position.

Job-to-job transition rate λ_e

An increase in the contact rate between firms and employed workers has two opposing effects on firms' profits. On the one hand, an existing worker is poached at a higher rate, which reduces the expected profit a firm can earn from the worker and thus decreases the offered wage. But on the other hand, there is more competition for workers and firms have an incentive to increase wage offers in order to retain their workforce. With a higher job-to-job transition rate, high-productivity firms are more able to poach employed workers from firms lower down in the productivity distribution. Since top firms are likely to gain workers while bottom firms are likely to lose them, top jobs will increase offered wage rates with an increase in λ_e, while the opposite is true for bottom jobs.

For high school graduates, employed men are 26% more likely to change jobs than employed women, and this implies that high school men are offered a wage rate that is 5 log-points higher than women at top firms. For college graduates, the job-to-job transition rates are quite comparable between men and women, and do not play a big role in the gender gap for wage offers.

Rate of within-job wage growth ρ

When within-job wage growth is high, workers are willing to accept a lower starting offer in order to enjoy greater growth in the future. Since low-productivity firms hire mainly from the unemployed pool of workers, they are most likely to reduce offered wage rates for the group of workers with a higher ρ. This decrease in offers at the lower end propagates upwards as the other firms do not need to pay as much to poach workers. The magnitude of the offer reduction diminishes as we move up the productivity distribution, as firms are less and less likely to hire from unemployment. Moreover, a higher human capital accumulation rate ρ implies that firms enjoy a more productive workforce and a higher level of output, especially in top jobs (due to production complementarity). Therefore, while bottom jobs are likely to reduce wage offers in response to a higher ρ, the effect is almost reversed at the top.

While high school men and women have very similar on-the-job growth rate, college men face a much higher rate of on-the-job wage growth than college women. This implies that college women would have received an even lower wage offer if they were to have a ρ as high as men's — the offer would be 16 log-points lower in a bottom job and 7 log-points lower in a median job. In Section 5.3 we show that this negative effect on wage offers will be more than compensated by the positive effect on human capital accumulation over the life-cycle.

Fertility parameters

Men and women differ in fertility rate γ_1, in the probability of getting job protection η, and in parental leave duration under protected and unprotected leave, γ_2 and γ_3. Fertility-related interruptions reduce expected firm profits because the worker does not contribute to firm output while on parental leave, and the firm has to incur search costs to recruit new workers. The higher the fertility rate and the longer the PL, the higher the costs to firms and thus the lower the wage offer will be. Instead, job-protected PL allows workers to go back to their previous employers and allows firms to retain their trained workforce, so higher η also has a positive effect on offered wage rates.

The positive effect of fertility parameters on wage offers is especially strong at the lower-end of the productivity distribution where firms hire mostly from unemployment. The reason is the higher reservation rate of unemployed men — they have a lower fertility rate then women and therefore place a lower value on the possibility of job protection that employment entails. All these gender differences tend to induce firms to offer lower wage rates to women than men, and the magnitudes are sizable for both education groups.

5.2.3 Steady-state wage-setting by firms: Summary

To recap, we can summarize Figure 6 and Figure 7 as follows. First, firms responses to gender differences in parameters are not uniform across the productivity range, in terms of both sign and magnitude. Second, for both education groups firms throughout the productivity range are ready to offer men higher wage rates than women. However, the reasons behind the offers gender gap differ by education. For the high-school group, the gap is mainly driven by the gender difference in job-finding rate λ_u, and for college group, the gap is mainly driven by the difference in the separation rate δ between men and women. Gender differences in fertility-related career interruptions are the second-important driver of offers gap in both education groups. Third, for college-graduates, gender differences in the rate of human capital accumulation actually moderate the offers gap in low-productivity firms, because a higher rate of on-the-job wage growth lowers the reservation cutoff of the unemployed men. Finally, the gap in wage rates offers is on average wider in the high-school group than in the college group, especially in low-productivity jobs. This is mostly due to the offsetting effect of differences in ρ on the offers gender gap for the college-educated workers, especially pronounced at the lower end of the jobs range.

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

5.3 Evolution of gender wage gaps over the life-cycle

Recall that at each point in the life-cycle, workers' wages are a combination of the current wage rate drawn from the steady-state offer distributions outlined in Section 5.2, as well as 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 firm, it also affects the speed at which men and women advance through the firm hierarchies and the amount of time they spend working and learning on-the-job. In this section, we describe how firm-specific wage premia translate into the gender wage gap over the life-cycle, and how they compare with the human capital channel.

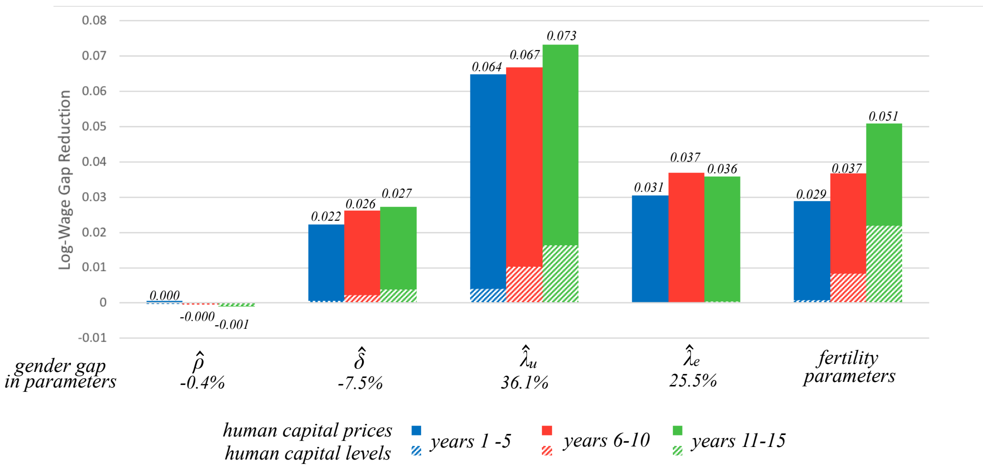
Figure 8 shows the extent to which each parameter contributes to the gender wage gap at different points of the life-cycle. The numbers on the top (bottom) of the bars indicate the increase (decrease) in women's wages if women were to have men's parameter value. The portion of the bar in striped color show the amount of wage increase (decrease) because of human capital gains (losses), and the portion in solid color shows the wage change due to changes in firm-specific wage rates: the price per unit of human capital.

Firms' equilibrium offers are a major factor of the gender wage gap in both the high- and low-skill labor markets throughout the life-cycle. Figure 8 shows that the parameters affect the gender wage gap through the firms' premia channel much more than the human capital channel. As expected, the role of human capital is bigger in later parts of the life-cycle. This is because the effect of skills is cumulative over time.

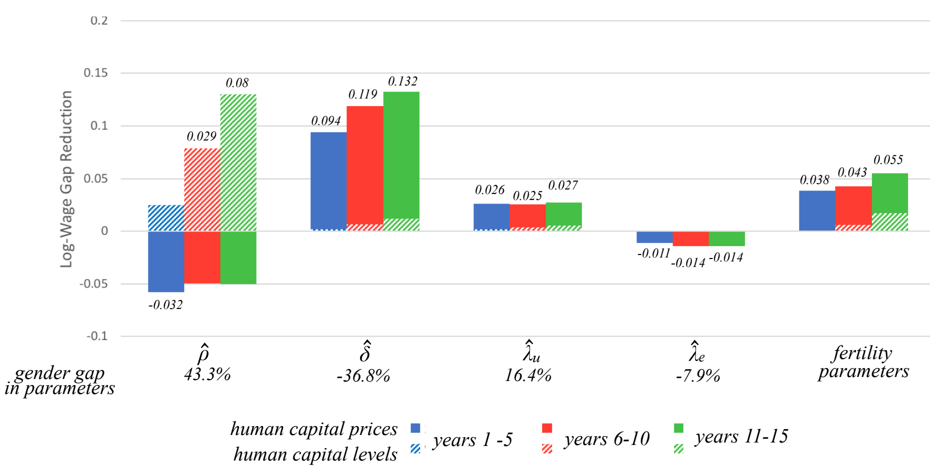
Note that the gender wage gaps are driven by different forces for the high school and college groups. For high school graduates, women's low job-finding rate and fertility-related interruptions are main sources of the wage gap. These gender differences not only cause employers to offer lower wage rates to women compared to men in the same firm (the effect we explored in the previous section, Section 5.2.2), they also make women advance more slowly through the hierarchy of firms. Additionally, the longer unemployment durations and fertility interruptions of women, imply that

Figure 8: Components of the gender gap over the life-cycle

(a) High school graduates



(b) College graduates



Notes: The figure shows the contribution of each parameter to the gender wage gap at different point of the life-cycle. The length of each bar corresponds to the total reduction of the wage gap (a negative height corresponds to an expansion of the gap). The striped portion of the bars show their contribution through changes in the levels of human capital while the solid portions denote the contributions through changes in the prices of human capital.

they lag behind men in human capital over time, even though high school men and women have very similar human capital growth rates.

For college graduates, the gender wage gap is predominantly driven by the higher separation rate of women and the higher human capital growth rate of men. Interestingly, college women's high quit rate and fertility interruptions do not affect their human capital accumulation by much since these events are rare and short-lived relative to the high-school group, but the career breaks do induce firms to offer substantially lower piece rates to women. What matters for college women's human capital is its slower growth rate ρ compared to men during employment spells, and this is an important factor of the gender wage gap in late career for the college group. The gender difference in ρ might be driven by a variety of reasons, e.g. women might face fewer opportunities for on-the-job training than men, women might put more effort in the family than in 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.

For both high school and college graduates, addressing the human capital channel alone would not be enough to close the gender wage gap. Women face a career cost of having children, but only a small part of it is due to forgone human capital gains during parental leaves. The main negative impact of fertility on women's wages comes from employers' offer responses in anticipation of fertility events. It is important for policies to improve women's labor force attachment i.e. by reducing their quit rates and increasing job-finding rates, so that firms change their expectations about men and women and offer similar piece rates across genders.

Note that if we were to sum the effects of all the parameters at a given point of the life-cycle, we would not eliminate the gap. This is because the effects of the parameters are not additive. We explore complementarities in Section 5.4 below.

5.4 Parameter interactions

In addition to eliminating a given gender difference in isolation, one can think of policies targeting a number of dimensions — for example, promoting more stable employment in conjunction with more training on-the-job, for female workers.

In this section, we explore how eliminating simultaneously a number of gender differences in parameters creates interactions between human capital levels and human capital prices in equilibrium. As a result, a combined policy can be much more effective than the sum of its parts.

To this end, we first divide the parameters into three groups: transition parameters $(\lambda_u, \lambda_e, \delta)$, fertility parameters $(\gamma_1, \gamma_2, \gamma_3, \eta)$ and the human capital accumulation parameter ρ. Then we use the model to simulate the impact of eliminating gender differences in two of the above parameter groups at a time. In Table 4 we compare the impact of these combined policies relative to targeting each parameter group in isolation and adding the effects.

As Table 4 illustrates, combining measures that improve job stability with measures that promote intensive human capital accumulation (ρ) creates sizable interactions on top of additive effects of the separate policies. For example, for the college group, eliminating gender differences in transitions in conjunction with gender differences in ρ would have a 17% higher impact on the gap compared to the situation when each dimension is equalized in isolation. In other words, a policy promoting stable employment would be enhanced when human capital accumulation rates are improved. Note that for the high-school group, we do not observe substantial interactions because in this group the gender differences in the human capital accumulation parameter ρ are negligible to start with.

Both supply and demand sides of the market play a role in the above complementarities. On the supply side, an increase in match stability (through transitions or fertility parameters) will bring about a more substantial increase in accumulated human capital (and therefore, wages), when ρ is increased. On the demand side, an increase in match stability will increase offered wage rates by more when ρ is high. This is because match profits go up by more in response to more stability when human capital accumulation is high — because firms have more time to enjoy workers' higher productivity.

Eliminating transitions and fertility differences simultaneously does not create any additional effects over and above an additive effect of the two policies, because these two parameter groups impact firms (and workers) in a similar way.

Table 4: *Parameter interactions*

	Combined effect of parameters with respect to the sum of the separate effects		
	(I) **Fertility and ρ**	(II) **Transitions and ρ**	(III) **Fertility and Transitions**
High school	0.97	0.99	0.99
College	1.08	1.17	0.98

Notes: This table reports the ratio between the combined effect of two out of three different channels of the model, and the sum of the corresponding separate effects. The channels we consider correspond to the transition parameters ($\lambda_u, \lambda_e, \delta$), the fertility parameters ($\gamma_1, \gamma_2, \gamma_3, \eta$) and the human capital accumulation parameter ρ. We use the model to simulate the impact of eliminating gender differences in two of the above parameter groups at a time and we compare the impact of these combined effects relative to targeting each parameter group in isolation and adding up the effects. Column (I) shows this ratio for the fertility parameters and the human capital accumulation parameter ρ, column (II) shows this ratio for the transition parameters and the human capital accumulation parameter ρ, and column (III) shows this ratio for the fertility and transition parameters.

6 Conclusion

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

We find that the differential wage rates set by the firms for men and women are a major source of the gender wage disparities, accounting for 55% of the gap for high school graduates and 47% for college graduates. These endogenous wage-setting decisions are an important transmission channel through which policies can impact individual labor market outcomes and the gender wage gap. For example, policies that alleviate fertility-related career interruptions have a sizable effect on the life-cycle gap. The model predicts that if women had the same patterns of fertility-related interruptions as men, the wage gap would narrow by approximately 19% at all levels of experience for both education groups, where most of the gap reduction will come from endogenous wage-setting responses of the firms. However, the most effective policies to reduce the gap in log-wages are those that improve women's labor market stability outside of the fertility events. For college educated women, equalizing the separation rate to that of men would close the gap by 50% on average over years 1-15 in a career. For high school graduates, equalizing the job finding rate across genders would close the gap by 25% on average over the same period. Moreover, increasing women's within job wage growth would enhance these effects.

The key insight of the model is that the two sides of the labor market determine the endogenous job ladder and we cannot predict the effect of a policy without filtering the forces exerted by both workers and firms through the model in equilibrium. To improve the labor market outcomes of women, we need a more holistic picture of how policies impact careers, and the framework developed in this paper takes a step in that direction.

Our model opens up a number of potentially important margins to take account of in empirical research on gender inequality. For example, possible extensions of our model might consider endogenizing the firm decisions to promote workers, to provide job-protected parental leave, and to hire or lay off a man versus a woman. These are important areas for future research, and our model is well-equipped to answer these questions especially with the availability of matched employer-employee data.

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A Data Appendix

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 C.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.

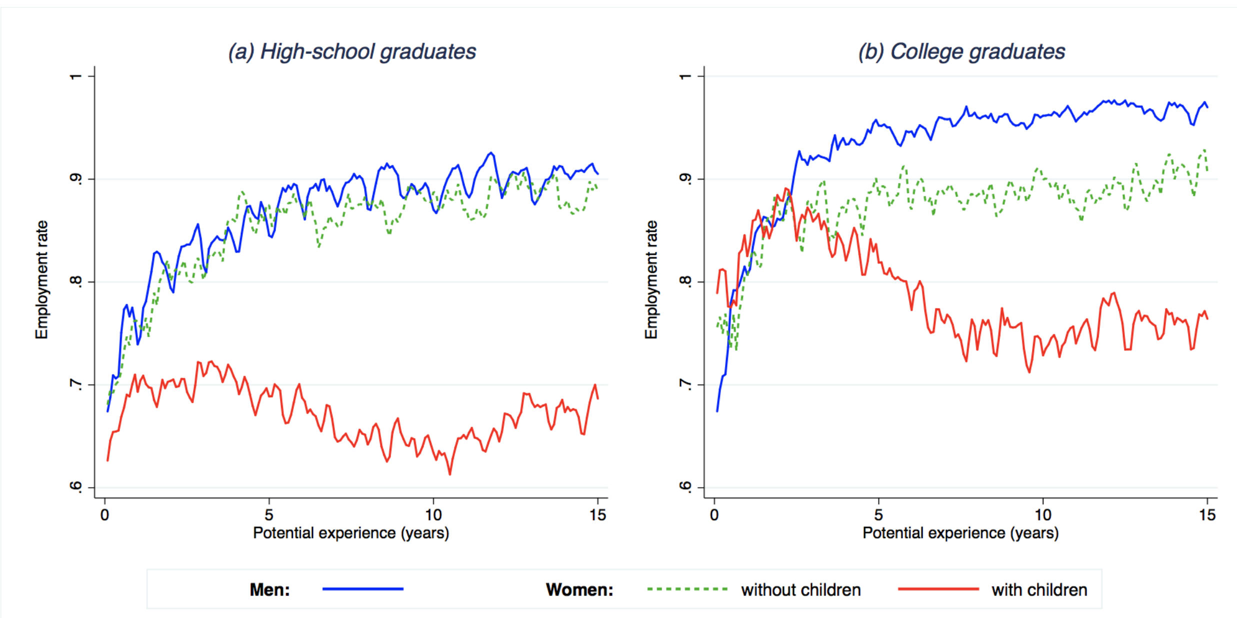
A.2 FMLA

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.[9] The data in Waldfogel (1999) show that no more than 40% of employees in medium to large firms[10] (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.

A.3 Employment rates by motherhood status

Figure 9: *Employment rates by motherhood status*



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

[9]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).

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

B Model Appendix

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

B.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 this worker is employed, $\frac{\partial y}{\partial t} = \rho y$. The dynamic component in the value function of employed workers is given by

$$\frac{\partial V(y,z)}{\partial t} = \frac{\partial V(y,z)}{\partial y}\rho y. \tag{10}$$

An important feature of equation (10) 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 (1) and (4), (4) and (2), we see that the value functions themselves are linear in y and can be expressed as

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

where α^U and α^{NJP} are numbers and $\alpha^E(z)$, $\alpha^{JP}(z)$ are some (yet unknown) functions of z. We show how to derive these expressions below.

B.2 Derivations: Worker's Side

In this Appendix we provide the proof of Proposition 1 restated below.

Proposition 1 *For a fixed $F(\cdot)$ with bounded and non-negative support, optimal job search implies that*

(i) $\alpha^E(z)$ *is the solution to the differential equation*

$$\frac{d\alpha^E(z)}{dz} = \frac{1}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}.\text{[11,12]} \tag{11}$$

(ii) $\left(\alpha^{NJP}, \alpha^{JP}(z^R), \alpha^U, z^R\right)$ *satisfy the following four equations,*

$$\alpha^{NJP} = \frac{b^{out}+\gamma_3\alpha^U}{r+\phi+\gamma_3}, \tag{12}$$

$$\alpha^{JP}(z) = \frac{b^{out}+\gamma_2\alpha^E(z)+\gamma_1\alpha^{NJP}}{r+\phi+\gamma_1+\gamma_2}, \tag{13}$$

$$\left[\zeta_1(\lambda_u-\lambda_e)-\rho\lambda_u+(r+\phi)\zeta_2\right]\alpha^U = \lambda_u z^R - \lambda_e b + \left[\zeta_2+\frac{\gamma_1(\lambda_u-\lambda_e)}{r+\phi+\gamma_3}\right]b^{out}, \tag{14}$$

$$\zeta_1\alpha^U = b+\frac{\gamma_1}{r+\phi+\gamma_3}b^{out}+\lambda_u\int_{z^R}^{\bar{z}}\frac{\overline{F}(z)}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}dz. \tag{15}$$

where $\zeta_1 = r+\phi+\gamma_1-\frac{\gamma_1\gamma_3}{r+\phi+\gamma_3}$, *and* $\zeta_2 = \frac{\lambda_u\gamma_1\eta(\gamma_3-\gamma_2)}{(r+\phi+\gamma_3)(r+\phi+\gamma_1+\gamma_2)}$. *Using the above four equations, the reservation wage* z^R *is implicitly defined by*

$$\zeta_1\left(z^R-b\right)+\frac{(r+\phi)\zeta_2}{\lambda_u}(b^{out}-b)+\rho\left(b+\frac{\gamma_1}{r+\phi+\gamma_3}b^{out}\right)$$
$$= \left[\zeta_1(\lambda_u-\lambda_e)-\rho\lambda_u+(r+\phi)\zeta_2\right]\int_{z^R}^{\bar{z}}\frac{\overline{F}(z)}{r+q(z)-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}dz. \tag{16}$$

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

$$(r+\phi)\alpha^U = b+\lambda_u\int_{z^R}^{\bar{z}}(\alpha^E(z)-\alpha^U)dF(z')+\gamma_1\cdot(\alpha^{NJP}-\alpha^U), \tag{17}$$

$$(r+\phi)\alpha^E(z) = z+\rho\alpha^E(z)+\lambda_e\int_z^{\bar{z}}(\alpha^E(z')-\alpha^E(z))dF(z') \tag{18}$$
$$+\gamma_1(\eta\alpha^{JP}(z)+(1-\eta)\alpha^{NJP}-\alpha^E(z))+\delta\left(\alpha^U-\alpha^E(z)\right),$$

---

[12]The boundary condition is

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

and given the boundary condition, the solution is unique.

[12]Recall, $q(z)$ denotes the total quit rate given by $q(z) = \phi+\delta+\gamma_1+\lambda_e\overline{F}(z)$.

$$(r+\phi)\alpha^{NJP} = b^{out} + \gamma_3 \cdot (\alpha^U - \alpha^{NJP}), \tag{19}$$

$$(r+\phi)\alpha^{JP}(z) = b^{out} + \gamma_2(\alpha^E(z) - \alpha^{JP}(z)) + \gamma_1(\alpha^{NJP} - \alpha^{JP}(z)) \tag{20}$$

Equations (19) and (20) yield (12) and (13) in Proposition 1.

Rearranging and differentiating (18) with respect to z,

$$\left(r-\rho+\gamma_1+\delta+\phi+\lambda_e\overline{F}(z)\right)\frac{d\alpha^E(z)}{dz} = 1+\gamma_1\eta\frac{d\alpha^{JP}(z)}{dz}. \tag{21}$$

Using the derivative of (13) with respect to z, we get the expression in (11). The boundary condition is obtained by evaluating (18) at the highest offer, $\bar{z}$.

Note that any unemployed worker would accept all offers above some reservation rate z^R, so her value in unemployment exactly equals the value of working under the lowest acceptable wage, i.e. she has a reservation rate strategy that satisfies $\alpha^E(z^R) = \alpha^U$. Evaluating the value function for the employed (18) at the reservation wage,

$$\begin{aligned}(r+\phi)\alpha^E(z^R) = z^R + \rho\alpha^U + \lambda_e\int_{z^R}^{\bar{z}}(\alpha^E(z') - \alpha^U)dF(z') \\ + \gamma_1\Big(\eta\alpha^{JP}(z^R) + (1-\eta)\alpha^{NJP} - \alpha^U\Big).\end{aligned}$$

(14) can be easily obtained by combining the above equation with (17). Finally, integrating (17) by parts yields equation (15).

Equations (11) to (15) in Proposition 1 make a system of five equations in five unknowns, z^R and α^U, given $F(z)$. Together they yield (16). □

Next, we obtain a useful expression for α^U, by evaluating the value function for the employed (18) at the reservation wage of the unemployed, z^R,

$$\begin{aligned}r\alpha^U = z^R + \rho\alpha^U + \lambda_e\int_{z^R}^{\bar{z}}(\alpha^E(z') - \alpha^U)dF(z') \\ + \gamma_1\Big(\eta\alpha^{JP}(z^R) + (1-\eta)\alpha^{NJP} - \alpha^U\Big) - \phi\alpha^U.\end{aligned}$$

Simplifying and using (17),

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

B.3 Characterization of Steady-State Measures and Distributions

In this section we provide details on the claims presented in Section 3.2.

Claim 1. i) *Workers are in one of four states while in the labor market*
$m_U + m_E + m_{JP} + m_{NJP} = 1,$

ii) *The flows into and out of* JP *balance*
$\eta \gamma_1 m_E = (\phi + \gamma_1 + \gamma_2) m_{JP},$

iii) *The flows into and out of employment balance*
$\lambda_u m_U + \gamma_2 m_{JP} = (\phi + \delta + \gamma_1) m_E,$ *and*

iv) *The flows into and out of unemployment balance*
$\phi + \delta m_E + \gamma_3 m_{NJP} = (\phi + \gamma_1 + \lambda_u) m_U.$

Proof. *(i)*, *(ii)* and *(iii)* can be easily established by equating inflows and outflows from each state in the economy.

Balancing inflow and outflow from unprotected maternity leave,

$$m_U \gamma_1 + (1-\eta)\gamma_1 m_E + \gamma_1 m_{JP} = (\phi + \gamma_3) m_{NJP}. \tag{22}$$

which together with *(i)*, *(ii)* and *(iii)*, imply that

$$\frac{m_E}{m_U} = \frac{\lambda_u}{\phi + \delta + \gamma_1 - \frac{\eta \gamma_1 \gamma_2}{\phi + \gamma_1 + \gamma_2}}.$$

Using *(ii)* in the equation above yields *(iv)*. □

Similarly, for a given level of experience x, the following balance-flow conditions must hold in equilibrium

i) The flows into and out of unemployment balance
$\phi + \delta m_E H(x) + \gamma_3 m_{NJP} N^{NJP}(x) = (\phi + \gamma_1 + \lambda_u) m_U N(x),$

ii) The flows into and out of employment balance
$\lambda_u m_U N(x) + \gamma_2 m_{JP} N^{JP}(x) = (\phi + \delta + \gamma_1) m_E H(x) + m_E \frac{dH(x)}{dx},$

iii) The flows into and out of *JP* balance
$\eta \gamma_1 m_E H(x) = (\phi + \gamma_1 + \gamma_2) m_{JP} N^{JP}(x),$

iv) The flows into and out of *NJP* balance
$\gamma_1 m_U N(x) + (1-\eta)\gamma_1 m_E H(x) + \gamma_1 m_{JP} N^{JP}(x) = (\phi + \gamma_3) m_{NJP} N^{NJP}(x)$, and

v) The flows into and out of employment with wage rates below z balance
$\lambda_u m_U N(x)F(z) + \gamma_2 m_{JP} H^{JP}(x,z) = q(z) m_E H(x,z) + m_E \frac{dH(x,z)}{dx}$.

Proposition 3. *The steady-state distributions are characterized below.*

i) *Distributions of experience x among unemployed and employed workers are, respectively,*

$$H(x) = 1 - e^{-\zeta_4 x}, \text{ and} \tag{23}$$

$$N(x) = 1 - \left(1 - \frac{\zeta_4}{\lambda_U}\frac{m_E}{m_U}\right) e^{-\zeta_4 x}, \tag{24}$$

where ζ_4 is given by

$$\zeta_4 = \frac{\phi(\phi+\gamma_3)\lambda_u}{[\phi(\phi+\gamma_1+\gamma_3)+\lambda_u(\phi+\gamma_3)]\, m_E}.$$

ii) *The distribution of experience among workers in parental leave with job protection is given by*

$$N^{JP}(x) = \frac{m_E}{m_{JP}}\left(\frac{\eta\gamma_1}{\phi+\gamma_1+\gamma_2}\right) H(x).$$

iii) *The distribution of experience among workers in parental leave without job protection is given by*

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

Proof. The inflow into employment over a small unit of time, dt, consists of workers with job protection finishing parental leave and coming back to their previous jobs, $m_{JP}N^{JP}(x)\gamma_2 dt$, and unemployed workers who have less than x units of experience who have found a job, $m_U N(x)\lambda_u dt$. The outflow from $H(x)$ over dt, consists of workers being fired, retiring, and getting a child shock, $m_E H(x)\,(\phi+\delta+\gamma_1)\,dt$, and workers who remain employed and whose experience grows above x during dt, $m_E\,(H(x+dt)-H(x))$. In addition there is some probability that both of the events conforming the outflow take place, but this possibility is of second order of magnitude relative to dt, we denote it by $O(dt^2)$.

Balancing inflow and outflow,

$$\left(\gamma_2\, m_{JP} N^{JP}(x) + \lambda_u\, m_U N(x)\right) dt = m_E\left[\,(\phi+\delta+\gamma_1)\, H(x)dt + (H(x+dt)-H(x))\,\right]$$

$$+O(dt^2).$$

Using equation (24), *(ii)* and taking dt to zero, yields a first order ordinary differential equation of $H(x)$ with initial condition $H(0)$ that can be written as

$$\zeta_4 = \zeta_5 H(x) + \frac{dH(x)}{dx}$$

where

$$\zeta_5 = (\phi+\delta+\gamma_1) - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \frac{\left(\delta\,(\phi+\gamma_3) + \left(\frac{\gamma_1+(1-\eta)(\phi+\gamma_2)}{\phi+\gamma_1+\gamma_2}\right)\gamma_1\gamma_3\right)\lambda_u}{\lambda_u\,(\phi+\gamma_3)+\phi\,(\phi+\gamma_1+\gamma_3)}$$

and, in fact, $\zeta_4 = \zeta_5$. Using as integrating factor $e^{\zeta_5 x}$ yields equation (23).

Next, we characterize $N(x)$. The inflow into unemployment consists of all new-born workers, ϕ, employed workers who get separated from their jobs and who have experience less than x, $\delta\, m_E H(x)$, and workers without job protection who have experience less than x and who get an alleviation shock γ_2, $\gamma_2\, m_{NJP} N^{NJP}(x)$. The outflow consists of unemployed workers with experience less than x finding jobs, getting fertility shocks or retiring, $(\phi+\gamma_1+\lambda_u)\, m_U N(x)$. Balancing inflow and outflow yields,

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

Rearranging yields equation (24).

Next, consider the distribution of experiences among workers in parental leave with job protection, $N^{JP}(x)$. The inflow to this state consists of employed workers with experience less than x getting fertility shock with job protection, $m_E H(x)\eta\gamma_1$ and the outflow are workers retiring (at rate ϕ), coming back to their previous jobs (at rate γ_2), or getting a second fertility shock γ_1 while in maternity leave. Balancing inflow and outflow yields *(ii)*.

Consider the share of unemployed workers whose experience is below x, $N(x)$. The inflow consists of all workers joining the workforce at rate ϕ together with employed workers whose match was destroyed and have experience less than x, i.e. $m_E H(x)\delta$, and workers who alleviate from maternity leave but had no job protection and have experience less than x so that they re-join the labor force in unemployment, $m_{NJP} N^{NJP}(x)\gamma_3$. The outflow consists of unemployed workers with experience less than x finding jobs, getting a fertility shock or retiring, i.e. $m_U N(x)\,(\phi+\gamma_1+\lambda_u)$. Balancing inflow and outflow yields *(iii)*. □

Proposition 4. *For a fixed $F(\cdot)$ with bounded and non-negative support, optimal job search implies that*

i) *The joint distribution of experiences and wage rates among employed workers $H(x,z)$ is given by*

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

where $s(z)=q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}$.

ii) *The joint distribution of experiences and wage rates among workers who are on parental leave with job protections coincides with the joint distribution of experiences and wage rates of employed workers,* $H^{JP}(x,z)=H(x,z)$.

Proof. The inflow into the pool of employed workers with experience less than x earning wage rate below z consists of unemployed workers who have experience less than x and who find a job at the wage rate below z, $m_U N(x)\lambda_u F(z)dt$; and workers with experience less than x coming back from protected maternity leave to their old employer who paid them wage rate below z, $m_{JP}\gamma_2 H^{JP}(x,z)dt$. The outflow from the pool $H(x,z)$ consists of workers in $H(x,z)$ retiring, separating into unemployment, getting child shock or finding better jobs, $m_E H(x,z)q(z)dt$ where $q(z)=\phi+\delta+\gamma_1+\lambda_e(1-F(z))$ and workers who remain employed at wage rate below z, but whose experience grows over dt and becomes just above x $m_E(H(x,z)-H(x-dt,z))$. Finally, there is a term that says that all these outflow events can happen simultaneously, but this probability is of the second order of magnitude relative to dt, we denote it by $O\left(dt^2\right)$. Balancing inflows and outflows

$$\begin{aligned}m_{JP}\gamma_2 H^{JP}(x,z)dt+m_U N(x)\lambda_u F(z)dt &= m_E H(x,z)q(z)dt+m_E\left(H(x,z)-H(x-dt,z)\right)\\ &\quad +O\left(dt^2\right).\end{aligned}$$

Using $\frac{\eta\gamma_1 m_E}{\phi+\gamma_1+\gamma_2}=m_{JP}$,

$$\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}H^{JP}(x,z)+\frac{m_U}{m_E}N(x)\lambda_u F(z)=H(x,z)q(z)+\frac{\partial H(x,z)}{dx}. \tag{25}$$

Note that the inflow into job-protected maternity leave are employed workers getting a fertility shock with job protection, $\gamma_1\eta m_E H(x,z)$ and the outflow are workers in $H^{JP}(x,z)$ retiring (ϕ), getting a fertility shock while in maternity leave (γ_1), or coming back to their old employer (γ_2). Balancing inflow and outflow,

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

which using *(ii)* from Claim 1 yields *(ii)*.

Using *(ii)*, (25) becomes a first order differential equation of $H(x,z)$ with initial condition $H(0,z) = 0$, which, using as integrating factor $e^{\left(q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)x}$, yields *(i)*. □

B.4 Derivations: Firm's Side

To solve for the equilibrium and show that the policy function $\xi(p)$ is defined by equation (26), we start by providing closed form expressions for the profit function of a firm of productivity p from posting an offer z,

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

where, recall, $y^{init}(z)$ denotes the the expected productivity with which a new hire will start her career at the firm, and $y^{acc}(z)$ denotes the human capital that accumulates from the workforce hired at wage rate z in the firm.

The first term, $y^{init}(z)$ is given by

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

Since the pool of potential hires consists of both employed and unemployed workers, where the first term describes the average human capital of workers recruited from the pool of unemployed, and the second term refers to workers poached from firms paying a wage rate below z. Recall that workers are heterogeneous in their initial productivity ε with exogenous distribution $A(\varepsilon)$. Here we denote expected initial productivity by $\widetilde{\varepsilon}$ and

$$\int_0^\infty e^{\rho x'} dN(x') = \frac{\zeta_4}{\zeta_4-\rho}\left(\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right),$$

and

$$\int_{z^R}^{z}\int_0^\infty e^{\rho x'} d^2H(x',z') = \frac{m_U}{m_E}\cdot\frac{\lambda_u F(z)}{q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}\left[1+\frac{n_2\rho}{(\zeta_4-\rho)}\right].[13]$$

Therefore,

$$y^{init}(z) = \frac{\widetilde{\varepsilon} m_U\lambda_u\zeta_4}{\zeta_4-\rho}\left(\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right)\left(\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho+\lambda_e}{q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}\right).$$

[13] Recall that $n_2 = 1-\frac{\zeta_4}{\lambda_u}\frac{m_E}{m_U}$.

Let us denote

$$M(z) = q(z) - \frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2} - \rho, \text{ and}$$

$$\zeta_6 = \frac{\widetilde{\varepsilon} m_U \lambda_u \zeta_4}{\zeta_4 - \rho}\left(\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right)\left(\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho+\lambda_e\right),$$

so that $y^{init}(z) = \zeta_6/M(z)$. We now turn to simplify the expression for $y^{acc}(z)$ given in equation (6) that allows us to write the firm's problem as in equation (7).

Note that the accumulated human capital at the firm depends on the duration of the match with the members of its workforce. For a match lasting τ periods, the worker accumulates the stream $\int_0^\tau e^{\rho t}dt$ of human capital.[14] The firm thus reaps the benefits from this accumulated human capital with some probability: the probability of a match lasting τ periods. Note that if the match ends after τ periods with job-protected maternity leave, with some probability, the worker will come back to her previous job in period τ' at which point, the match "resets" and the firm can reap benefits from the accumulation of human capital of this worker in this "second" job-spell at the firm. Algebraically, let $(P_1(\tau)+P_2(\tau))$ denote the probability that the match lasts exactly τ periods, with $P_1(\tau)$ denoting the probability that the match lasts τ and is terminated for reasons other than fertility with job protection, and $P_2(\tau)$, the probability that the match lasts τ, and is terminated job-protected fertility, in which case, with probability $P_3(\tau')$, the worker will come back to her previous job in period τ'. Then,

$$y^{acc}(z) = \int_{\tau=0}^{\infty}\left((P_1(\tau)+P_2(\tau))\int_0^\tau e^{\rho t}dt \;+\; P_2(\tau)e^{\rho\tau}\int_{\tau'=0}^{\infty}P_3(\tau')y^{acc}(z)d\tau'\right)d\tau.$$

Where the probability that the match lasts τ and is terminated for reasons other than job-protected fertility is $P_1(\tau) = \left(\phi+\delta+\gamma_1(1-\eta)+\lambda_e\overline{F}(z)\right)e^{-q(z)\tau}$, the probability that the match lasts τ, and is terminated job-protected fertility is given by $P_2(\tau) = \eta\gamma_1 e^{q(z)\tau}$, and the probability that the worker will come back to her previous job in period τ' is given by[15] $P_3(\tau') = \gamma_2 e^{-\gamma_2\tau'}e^{-(\phi+\gamma_1)\tau'}$.

[14]Suppose that the worker may have entered the firm with human capital $y = \varepsilon e^{\rho x_0}$. If she works for exactly τ periods, her human capital increases to $\bar{y} = \varepsilon e^{\rho(x_0+\tau)}$, and from this one particular worker, the firm would have earned profits $\varepsilon e^{\rho(x_0+t)}(p-z)$ at each "instant" $t \in (0,\tau)$. Thus, the contribution of this one worker to $y^{acc}(z)$ would be

$$\frac{\varepsilon e^{\rho(x_0+t)}(p-z)}{(p-z)\varepsilon e^{\rho x_0}} = \frac{\varepsilon e^{\rho(x_0+t)}}{\varepsilon e^{\rho x_0}} = e^{\rho t} \quad \text{for each "instant"} \quad t\in(0,\tau),$$

or $\int_0^\tau e^{\rho t}dt$.

[15]Note that it is immaterial — for $y^{acc}(z)$, — to consider the time before the worker actually comes back to the job as no human capital is accumulated while she is in PL. Thus, rather than considering the actual period $\tilde{\tau} > \tau$ in which the worker rejoins the labor market, we simply restart counting her tenure at the job with a $\tau' \in \mathbb{R}^+$.

Thus yielding the following recursive expression for $y^{acc}(z)$,

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

So that $y^{acc}(z) = 1/M(z)$ and

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

Where $\ell(z) = \frac{\zeta_6/M(z)}{M(z)} = \frac{\zeta_6}{M(z)^2}$ is strictly increasing in z, implying that the optimal wage policy is increasing in p and more productive firms post higher wage offers. This proves part *(ii)* of Proposition 2.

Recall that we denote the optimal wage rate offer function by $\xi(p)$. In equilibrium, for any $z \in [z^R, \bar{z}]$, $F(z) = F(\xi(p)) = \Gamma(p)$. Let the profits from posting an optimal offer $\xi(p)$ 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

$$\begin{aligned}
\xi(p) &= p - \frac{\pi^*(\xi(p))}{\ell(\xi(p))} \\
&= p - \frac{\int_{z^R}^{p}\frac{\zeta_6}{M(\xi(x))^2}dx}{\frac{\zeta_6}{M(\xi(p))^2}} \\
&= p - M(\xi(p))^2\int_{z^R}^{p}\frac{1}{M(\xi(p'))^2}dp'. \qquad (26)
\end{aligned}$$

The above equation gives the optimal wage policy of a firm of productivity p, given the reservation wage rate of workers, z^R. This proves part *(i)* of Proposition 2. Notice that we should separately regard the case in which $z^R < \underline{p}$, where

$$\frac{\pi^*(\xi(p))}{\ell(\xi(p))} = \frac{\frac{(\underline{p}-z^R)}{M(\xi(\underline{p})^2} + \int_{\underline{p}}^{p}\frac{1}{M(\xi(x))^2}dx}{\frac{1}{M(\xi(p))^2}}, \qquad (27)$$

and

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

We obtain an additional equation on z^R and $\Gamma(p)$ to close the system in Proposition 5 below.

Proposition 5. *The following equation characterizes z^R,*

$$\begin{aligned}\tfrac{(\gamma_3-\gamma_2)\gamma_1\eta}{r+\phi+\gamma_1+\gamma_2}\left(b^{out}-b\right) = \left(b-z^R\right)(r+\phi+\gamma_1+\gamma_3) - \rho\frac{b(r+\phi+\gamma_3)+\gamma_1 b^{out}}{r+\phi} \\ + \zeta_7\left[\frac{\left(\underline{p}-z^R\right)}{M(\xi(\underline{p}))^2}\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(\xi(x))+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\Psi(x)dx\right. \\ \left.+\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(\xi(x))+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\left(\int_{\underline{p}}^{x}\frac{1}{M(\xi(r))^2}dr\right)\Psi(x)dx\right]\end{aligned}$$

with $\zeta_7 = (\lambda_u-\lambda_e)(r+\phi+\gamma_1+\gamma_3) - \frac{\rho(r+\phi+\gamma_3)\lambda_u}{r+\phi} + \frac{(\gamma_3-\gamma_2)\eta\lambda_u\gamma_1}{r+\phi+\gamma_1+\gamma_2}$ *and* $\Psi(p) = 2\lambda_e\Gamma'(p)M(\xi(p))$.

Proof. We prove the claim by combining the $\xi(p)$ from above with equation (16), changing the variable of integration from z to p, using the formula: $\int_{\phi(a)}^{\phi(b)} f(x)dx = \int_a^b f(\phi(t))\phi'(t)dt$,

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

Using the equation for optimal wage function (26), we find the derivative $\xi'(p)$ given by

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

where $\Psi(p) = 2\lambda_e\Gamma'(p)M(\xi(p))$. Summing up using (16),

$$\begin{aligned}\frac{(\gamma_3-\gamma_2)\gamma_1\eta}{r+\phi+\gamma_1+\gamma_2}\cdot\left(b^{out}-b\right) = \left(b-z^R\right)(r+\phi+\gamma_1+\gamma_3) - \rho\frac{b(r+\phi+\gamma_3)+\gamma_1 b^{out}}{r+\phi} \\ + \zeta_7\int_{z^R}^{\bar{z}}\frac{\overline{F}(z)}{\left(q(z)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\end{aligned}$$

where

$$\zeta_7 = (\lambda_u-\lambda_e)(r+\phi+\gamma_1+\gamma_3) - \frac{\rho(r+\phi+\gamma_3)\lambda_u}{r+\phi} + \frac{(\gamma_3-\gamma_2)\eta\lambda_u\gamma_1}{r+\phi+\gamma_1+\gamma_2}.$$

Then, using (28),

$$\frac{(\gamma_3-\gamma_2)\gamma_1\eta}{r+\phi+\gamma_1+\gamma_2}\cdot\left(b^{out}-b\right)=\left(b-z^R\right)(r+\phi+\gamma_1+\gamma_3)-\rho\frac{b(r+\phi+\gamma_3)+\gamma_1 b^{out}}{r+\phi}$$
$$+\zeta_7\left[\frac{\left(\underline{p}-z^R\right)}{M(\xi(\underline{p}))^2}\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\Psi(x)dx\right.$$
$$\left.+\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\left(\int_{\underline{p}}^{x}\frac{1}{M(\xi(r))^2}dr\right)\Psi(x)dx\right].$$

□

We can rewrite this expression so that z^R appears on both sides using $\xi_1'(p)$ and $\xi_2'(p)$,

$$(r+\phi)\left(\frac{r+\phi+\gamma_3+\gamma_1}{r+\phi+\gamma_3}\right)\frac{\lambda_u z^R-\lambda_e b+\frac{\gamma_1\lambda\_u\eta b^{out}}{r+\phi+\gamma_1+\gamma_2}+\left[(\lambda_u-\lambda_e)-\frac{\eta\lambda_u(r+\phi+\gamma_2)}{r+\phi+\gamma_1+\gamma_2}\right]\frac{\gamma_1 b^{out}}{r+\phi+\gamma_3}}{(\lambda_u-\lambda_e)\left(r+\phi+\gamma_1-\frac{\gamma_1\gamma_3}{r+\phi+\gamma_3}\right)-\rho\lambda_u+\frac{(r+\phi)(\gamma_3-\gamma_2)}{r+\phi+\gamma_3}\frac{\eta\lambda_u\gamma_1}{r+\phi+\gamma_1+\gamma_2}}$$
$$=b+\frac{\gamma_1 b^{out}}{r+\phi+\gamma_3}$$
$$+\lambda_u\left(\frac{\left(\underline{p}-z^R\right)\zeta_6}{\phi+\delta+\gamma_1+\lambda_e-\rho-\frac{\gamma_1\gamma_2\eta}{\phi+\gamma_1+\gamma_2+c}}\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\xi_1'(x)dx\right.$$
$$\left.+\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\xi_2'(x)dx\right). \tag{30}$$

(30) gives the explicit solution for z^R, given the parameters and the distribution of productivities $\Gamma(p)$. Once z^R has been solved for, for each $p\in\left[\underline{p},\overline{p}\right]$ we find the corresponding optimal $z=\xi(p)$ using (26).

C Details of Estimation

C.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

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

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},

$$D_{EtoU} = \frac{\delta}{\phi + \delta + \gamma_1} \left(1 - e^{-(\phi+\delta+\gamma_1)}\right). \tag{32}$$

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

$$\mathbb{E}(JP \text{ duration}) = \frac{1}{\phi + \gamma_1 + \gamma_2}. \tag{33}$$

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, $\mathbb{E}(NJP$ 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,

$$\mathbb{P}(\text{Come back}) = \frac{\eta \gamma_2}{\phi + \gamma_1 + \gamma_2}. \tag{34}$$

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,

$$\begin{aligned} D_{EtoE}(z) &= \int_0^1 \lambda_e(1 - F(z))\, e^{-\lambda_e(1-F(z))\tau} e^{-(\phi+\delta+\gamma_1)\tau} d\tau \\ &= -\frac{\lambda_e(1 - F(z))}{\phi + \delta + \gamma_1 + \lambda_e(1 - F(z))}\, e^{-(\phi+\delta+\gamma_1+\lambda_e(1-F(z)))\,\tau}\Big|_0^1 \end{aligned}$$

$$= \frac{\lambda_e(1-F(z))}{\phi+\delta+\gamma_1+\lambda_e(1-F(z))}\left(1-e^{-(\phi+\delta+\gamma_1+\lambda_e(1-F(z)))}\right)$$
$$= \frac{\lambda_e(1-F(z))}{q(z)}\left(1-e^{-(\phi+\delta+\gamma_1+\lambda_e(1-F(z)))}\right),$$

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

$$D_{EtoE}|x = \int_{\underline{z}}^{\overline{z}} D_{EtoE}(z)dH(z|x), \tag{35}$$

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 $F(z)$.[16] 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

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

[16] 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 $\underline{z}$.

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

$$
\begin{aligned}
H(z|x)dz = \frac{(\phi+\delta+\gamma_1-\omega)}{H(x)} \Bigg[& \left(\frac{1-e^{-s(z)x}}{s(z)} - \frac{n_2(e^{-Rx}-e^{-s(z)x})}{s(z)-R} \right) \\
& - \lambda_e F(z) \left(e^{s(z)x} \left\{ \frac{-xs(z)+1}{(s(z))^2} - n_2 \frac{x(s(z)-R)+1}{(s(z)-R)^2} \right\} \right. \\
& \left. - \frac{1}{(s(z))^2} - \frac{e^{-R}}{(s(z)-R)^2} \right) \Bigg] f(z)dz
\end{aligned}
$$

because $q'(z) = -\lambda_e f(z)$. To algebraically show that (35) does not depend on $F(z)$, following Hornstein et al. (2011), consider the change of variable given by $t = F(z)$ so that $(F^{-1})'(t) = \frac{1}{f(z)}$. It follows that

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

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

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

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

with

$$
D_{EtoE}(t) = \frac{\lambda_e(1-t)}{\tilde{q}(t)} \left(1 - e^{-(\phi+\delta+\gamma_1+\lambda_e(1-t))} \right).
$$

Therefore,

$$
\begin{aligned}
D_{EtoE}|x = & \int_{\underline{z}}^{\bar{z}} \frac{\frac{\lambda_e(1-F(z))}{q(z)}\left(1-e^{-q(z)}\right)F'(z)}{e^{-(q(\bar{z})-\omega)x}+\frac{n_2\left(Re^{-Rx}-(q(\bar{z})-\omega)e^{-(q(\bar{z})-\omega)x}\right)}{q(\bar{z})-\omega-R}} \\
& \times\left[\left(e^{-(q(z)-\omega)x}+\frac{n_2\left(Re^{-Rx}-(q(z)-\omega)e^{-(q(z)-\omega)x}\right)}{q(z)-\omega-R}\right)\right. \\
& \quad +F(z)\lambda_e\left(e^{-(q(z)-\omega)x}x+\frac{n_2Re^{-Rx}}{(q(z)-\omega-R)^2}\right. \\
& \quad \left.\left. -n_2e^{-(q(z)-\omega)x}\left[\frac{(q(z)-\omega)x(q(z)-\omega-R)+R}{(q(z)-\omega-R)^2}\right]\right)\right]dz \\
= & \int_{\underline{z}}^{\bar{z}} \frac{\frac{\lambda_e(1-t)}{q(t)}\left(1-e^{-\tilde{q}(t)}\right)}{e^{-(\phi+\delta+\gamma_1-\omega)x}+\frac{n_2\left(Re^{-Rx}-(\phi+\delta+\gamma_1-\omega)e^{-(\phi+\delta+\gamma_1-\omega)x}\right)}{\phi+\delta+\gamma_1-\omega-R}} \\
& \times\left[\left(e^{-(q(t)-\omega)x}+\frac{n_2\left(Re^{-Rx}-(\tilde{q}(t)-\omega)e^{-(\tilde{q}(t)-\omega)x}\right)}{\tilde{q}(t)-\omega-R}\right)\right. \\
& \quad +t\lambda_e\left(e^{-(q(t)-\omega)x}x+\frac{n_2Re^{-Rx}}{(q(t)-\omega-R)^2}-\right. \\
& \quad \left.\left. -n_2e^{-(\tilde{q}(t)-\omega)x}\left[\frac{(\tilde{q}(t)-\omega)x(\tilde{q}(t)-\omega-R)+R}{(\tilde{q}(t)-\omega-R)^2}\right]\right)\right]dt
\end{aligned}
$$

which does not depend on F.

$$
\begin{aligned}
\text{Job Duration} &= K\left[\begin{array}{c}\left[\frac{\phi+\gamma_1+\gamma_2}{\eta\gamma_1\gamma_2}\right]^2\frac{1}{\lambda_e}\ln\left(\frac{\phi+\delta+\gamma_1+\lambda_e}{\phi+\delta+\gamma_1}\frac{\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}{\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}}\right) \\ +\frac{\phi+\gamma_1+\gamma_2}{\eta\gamma_1\gamma_2}\frac{1}{\left(\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)\left(\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)}\end{array}\right] \\
\text{where } K &= \left(\phi+\delta+\gamma_1-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right)\left(\phi+\delta+\gamma_1+\lambda_e-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}\right) \qquad (36)
\end{aligned}
$$

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.

C.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 C.3 below.

C.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 C.3.1 to C.3.6 we detail how we derive the model implied moments we use for estimation.

C.3.1 Mean log wage by actual experience

Mean log-wages conditional on actual experience are given by

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

C.3.2 Variance of log wage by actual experience

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

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

where lines 6 to 7 in the equation above follow since $\mathbb{E}\left[\left(\log z - \mathbb{E}(\log z|x)\right)\big|x\right] = 0$. The derivative of the conditional distribution $H(z|x)$ with respect to the wage rate z is given by,

$$\frac{dH(z|x)}{dz} = \frac{f(z)}{e^{-(q(\bar{z})-\omega)x} + \frac{n_2\left(R_1 e^{-R_1 x} - (q(\bar{z})-\omega)e^{-(q(\bar{z})-\omega)x}\right)}{q(\bar{z})-\omega-R_1}}$$

$$\times \left[\begin{array}{c} e^{-(q(z)-\omega)x} + \frac{n_2 R_1 e^{-R_1 x}}{q(z)-\omega-R_1} - \frac{n_2 e^{-(q(z)-\omega)x}}{1-\frac{R_1}{(q(z)-\omega)}} \\ +\lambda_e F(z) \left(\begin{array}{c} e^{-(q(z)-\omega)x} x + \frac{n_2 R_1 e^{-R_1 x}}{(q(z)-\omega-R_1)^2} - \\ -\frac{n_2 e^{-(q(z)-\omega)x}(x(q(z)-\omega)(q(z)-\omega-R_1)+R_1)}{[q(z)-\omega-R_1]^2} \end{array} \right) \end{array} \right], \tag{37}$$

where to avoid the numerical computation of the density $f(z)$ we use the equilibrium mapping between z and p, namely $F(z) = F(\xi(p)) = \Gamma(p)$, which implies that

$$f(z) = \frac{dF(z)}{dz} = \frac{\Gamma'(p)}{\xi'(p)}\Big|_{z=\xi(p)}$$

Note that from the equilibrium solution we have an analytical expression for $\xi'(p)$ (see equation (29)). It follows that,

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

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

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

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

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

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

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

where $\mathbb{E}(\log z'|z' > z)$ is the average offer conditional that it is higher than the current wage rate z.

This average offer depends on the distribution of offers $F(\cdot)$ and the current wage rate z,

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

so that

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

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

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

and hence

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

C.3.4 Skewness

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

$$\begin{aligned}
S(\log w|x) &= \mathbb{E}\left[\left(\frac{x - \mathbb{E}(x)}{\sigma(x)} \right)^3 \right] \\
&= \mathbb{E}\left[\left(\frac{\log w - \mathbb{E}(\log w|x)}{(Var(\log w|x))^{0.5}} \right)^3 |x \right] = \frac{\mathbb{E}\left((\log w - \mathbb{E}(\log w|x))^3 |x \right)}{(Var(\log w|x))^{3/2}} \\
&= \frac{\mathbb{E}\left([\log \varepsilon + \rho x + \log z - (\rho x + \mathbb{E}(\log z|x) + \mathbb{E}(\log \varepsilon))]^3 |x \right)}{(Var(\log w|x))^{3/2}} \\
&= \frac{\mathbb{E}\left([\log \varepsilon + \log z - \mathbb{E}(\log z|x) - \mathbb{E}(\log \varepsilon)]^3 |x \right)}{(Var(\log w|x))^{3/2}} \\
&= \frac{\mathbb{E}\left([\log z + \log \varepsilon - \mathbb{E}(\log \varepsilon) - \mathbb{E}(\log z|x)]^3 |x \right)}{(Var(\log w|x))^{3/2}}
\end{aligned}$$

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

C.3.5 Kurtosis

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

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

Note that the numerator of the expression above is given by

$$
\begin{aligned}
&E\left[(\log z - \mathbb{E}(\log z|x) + \log\varepsilon - \mathbb{E}(\log\varepsilon))^4\,|x\right] \\
&= \mathbb{E}\left[\left(\begin{array}{c} (\log z - \mathbb{E}(\log z|x))^4 + 4\,(\log z - \mathbb{E}(\log z|x))^3\,(\log\varepsilon - \mathbb{E}(\log\varepsilon)) \\ +6\,(\log z - \mathbb{E}(\log z|x))^2\,(\log\varepsilon - \mathbb{E}(\log\varepsilon))^2 + 4\,(\log z - \mathbb{E}(\log z|x))\,(\log\varepsilon - \mathbb{E}(\log\varepsilon))^3 \\ +(\log\varepsilon - \mathbb{E}(\log\varepsilon))^4 \end{array} \right) |x \right]
\end{aligned}
$$

$$
= \begin{bmatrix} E\left[\left(\log z-\mathbb{E}(\log z|x)\right)^4|x\right]+4E\left[\left(\log z-\mathbb{E}(\log z|x)\right)^3\left(\log\varepsilon-\mathbb{E}(\log\varepsilon)\right)|x\right] \\ +6E\left[\left(\log z-\mathbb{E}(\log z|x)\right)^2\left(\log\varepsilon-\mathbb{E}(\log\varepsilon)\right)^2|x\right]+4E\left[\left(\log z-\mathbb{E}(\log z|x)\right)\left(\log\varepsilon-\mathbb{E}(\log\varepsilon)\right)^3|x\right] \\ +\mathbb{E}\left[\left(\log\varepsilon-\mathbb{E}(\log\varepsilon)\right)^4|x\right] \end{bmatrix}
$$

$$
= \mathbb{E}\left[\left(\log z-\mathbb{E}(\log z|x)\right)^4|x\right]+6Var(\log z|x)Var(\log\varepsilon)+\mathbb{E}\left[\left(\log\varepsilon-\mathbb{E}(\log\varepsilon)\right)^4|x\right]
$$

$$
= \mathbb{E}\left[\left(\log z-\mathbb{E}(\log z|x)\right)^4|x\right]+6\left[Var(\log w|x)-Var(\log\varepsilon)\right]Var(\log\varepsilon)+\mathbb{E}\left[\left(\log\varepsilon-\mathbb{E}(\log\varepsilon)\right)^4|x\right]
$$

Thus, regrouping terms,

$$
K(\log w|x) = \frac{\begin{bmatrix} \int_{z^R}^{\bar{z}}\left(\log z-\log z^R-\int_{z^R}^{\bar{z}}\frac{1-H(z|x)}{z}dz\right)^4 dH(z|x)+6\left[Var(\log w|x)-Var(\log\varepsilon)\right]Var(\log\varepsilon) \\ +\int_{\underline{\varepsilon}}^{\bar{\varepsilon}}\left(\log\varepsilon-\mathbb{E}(\log\varepsilon)\right)^4 dA(\varepsilon) \end{bmatrix}}{\left[Var(\log w|x)\right]^2}
$$

C.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

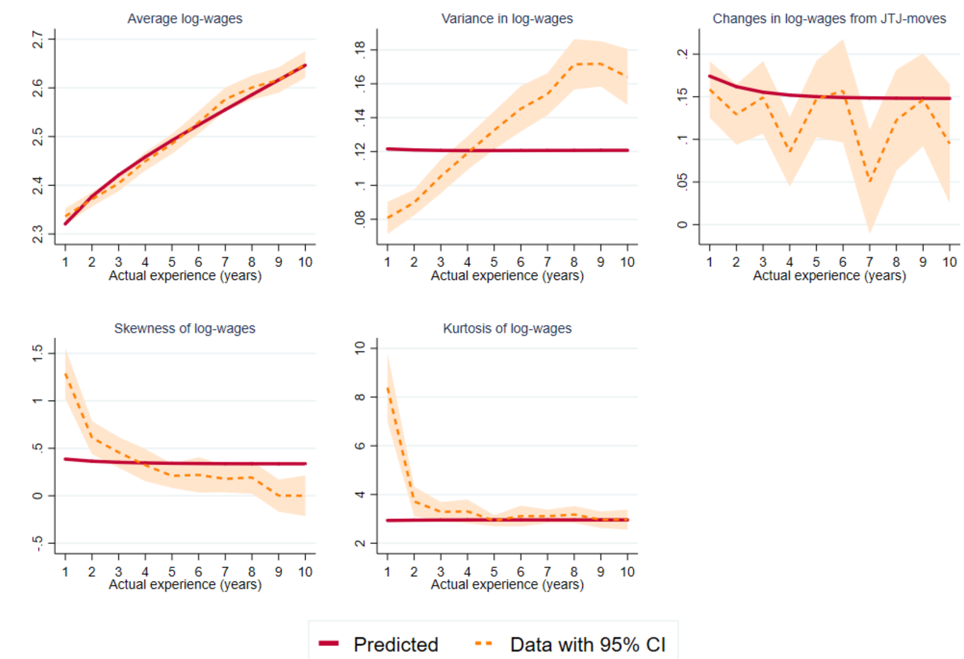
$$
\log(w^{\min}) = \log(\underbrace{\underline{\varepsilon}}_{=1})+\log(z^R) = \log(z^R).
$$

D Details of the Results

D.1 Women's estimates

Figure 10: *Fit of the targeted moments for women*

(a) *High-school graduates*

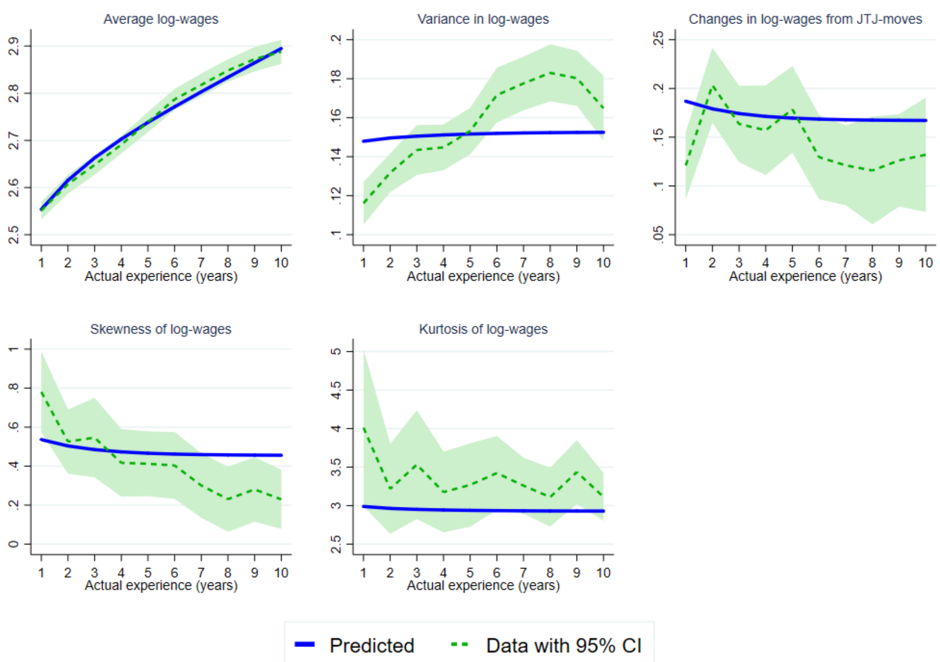


(b) *College graduates*

D.2 Men's estimates

Figure 11: *Fit of the targeted moments for men*

(a) *High-school graduates*



(b) *College graduates*