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Equilibrium Wage-Setting and the Life-Cycle Gender Pay Gap*

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Abstract

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

1 Introduction

There is a substantial wage gap between men and women and, notably, it expands over the life-cycle. There is an extensive literature that highlights gender differences in various dimensions of labor market behavior, and how they may hinder women's career progression.

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However, how do employers respond to these differences across genders? This paper studies the drivers of life-cycle wage divergence across genders, incorporating firms' decisions into the analysis.

Using the 1979 National Longitudinal Survey of Youth (NLSY79), we document that women are subject to more career interruptions due to childbirth and childcare, suggesting that they might accumulate less human capital than men over time. In particular, we find that women college graduates in the NLSY79 spend 16 months in fertility-related non-employment, while men spend only 0.5 months on average. Moreover, we find that women's labor market turnover is also different from men's outside of parental leave. For example, women are 58.5% more likely to exit employment than men, which could also reflect family concerns or childcare responsibilities. In order to quantify the response to these differences from the demand side of the labor market, we build a model in which firms make wage offer decisions based on average group characteristics. In other words, firms expect individual workers to follow the gender-specific patterns, and statistically discriminate workers by gender.

In order to decompose the life-cycle wage gap into labor supply and demand factors in a tractable way, we develop a dynamic search model of the labor market in which human capital is a homogenous good. Workers accumulate on the stock of human capital while employed, and firms set the price of the good to maximize expected profit. Men and women differ in several dimensions, such as turnover rates, parental leave lengths and human capital growth rates. In addition, some jobs can be available to both genders, while there might also be jobs that employ only men or only women. In a labor market with frictions, workers cannot be replaced immediately, and turnover is costly for firms. Employers take into account the costs and values implied by the above gender differences, and price the human capital of men and women accordingly. Such differential price-setting rules across gender will be referred to as statistical discrimination for the rest of the paper.

The structure of the model allows us to decompose the gender wage gap into three additive parts: the gap in accumulated human capital, the gap due to differences in the productivities of firms employing men and women, and the gap in wage-rates offered to men and women by equally productive firms. We find that over the first 15 years of a career, on average 27% of the gap is due to differences in human capital stocks, 28% is due to differences in the productivities of firms' that men and women match with, and 45% of the gap can be attributed to statistical discrimination. The importance of these three channels varies at different points of the life-cycle. The gap in human capital differences is cumulative and more than doubles from the start of workers' careers to 15 years later. This divergence of human capital paths explains 73% of the total wage gap expansion. Statistical discrimination also becomes more important later on in the life-cycle when workers reach higher rungs of the wage ladder, and explains 27% of the gap expansion. In contrast, the gap due to jobs segregation stays relatively constant over the 15 years.

We quantify the relative importance of labor market transitions, human capital accumulation rates, and parental leave durations and coverages on the gender wage gap, and find that labor market transitions have the largest effect in narrowing the gap. In particular, eliminating the differences in the separation rate reduces the gap by 57% on average. It not only allows women to gain human capital and receive higher wages in the long run, but also reduces firms' statistical discrimination throughout the life-cycle. The magnitude of the gap reduction would be underestimated by 80% if firms' responses are ignored, especially for younger women. Interestingly, when the human capital accumulation rate of women is increased to the level of men (a 20% increase), the gap increases by 14.1% in earlier years and decreases by 15.7% in later years. This is because women are willing to accept lower wages with a better accumulation technology, and their equilibrium wage rates go down. However, the gain in the human capital stock in the long run more than compensates for the loss in wage rates, so the net effect on women's wages is positive in late career.[1] On the other hand, parental leave generosity plays a relatively small role, and explain only 9.5% of the gender wage gap.

Finally, we successively eliminate structural differences between genders to analyze the complementarities between the different channels contributing to the gap. We find that an increase in human capital accumulation rate amplifies the effect of an increase in job stability. This is because when human capital accumulates faster, any increase in work experience due to more stable employment implies 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 with a better distribution of offers. Thus, equalizing transition rates together with the human capital accumulation technology, leads to a combined effect on the gap that is 11% larger than the sum of their separate effects. In contrast, since equalizing parental leave generosity does not lead to a substantial increase in the accumulation of actual experience nor in the expected match durations, the complementarity of this channel with human capital growth is quantitatively weaker.

1.1 Related Literature

For the most part, recent literature has focused on empirically quantifying the relative roles of human capital accumulation and mobility differences between male and female workers.

[1] We describe the effects of changes in all parameters in Section 5.

Manning and Swaffield (2008), Del Bono and Vuri (2011), Goldin, Kerr, Olivetti, Barth et al. (2017) and Barth, Kerr, and Olivetti (2017) find that differences in the returns to job mobility and returns to experience account for most of the gender earnings gap 15 years after leaving school. We formalize these two channels in a theoretical framework and take a first step in endogenizing firms' equilibrium wage offer distributions for men and women.[2] Furthermore, by explicitly modeling women's career interruptions when having children, we also contribute to the literature about women's career costs of having children.

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. Importantly, these papers model the workers' choices given an exogenous distribution of wage offers. In contrast, we allow firms to consider different labor market behaviors of men and women, which lead employers to offer different wage rate menus to male and female workers in equilibrium. In an analysis closely related to this paper, Bartolucci (2013) builds a search model with rent-splitting and asks how much of the gender wage gap can be explained by differences in productivity, frictions, segregation and wage discrimination. Our work differs from Bartolucci (2013) in that we focus on the life-cycle, we introduce human capital dynamics and explicitly include fertility and job protection in the model. Importantly, the analysis of discrimination is different in Bartolucci (2013), who interprets it as differences in the rent-splitting parameter, whereas in our framework discrimination is statistical and is reflected in the different wage ladders set by the firms in equilibrium.

In concurrent work, both Bagger, Lesner, and Vejlin (2019) and Moser and Morchio (2019) undertake a structural exercise linking the gender gap to the role of firms in the labor market. Moser and Morchio (2019) use matched employer-employee data in Brazil to decompose the gender gap into gender differences in job-to-job mobility versus firm heterogeneity in amenities and employers' gender preferences. There are several crucial differences between our studies. First, we focus on the *evolution* of the gender wage gap over the life-cycle and incorporate human capital accumulation. Second, we explicitly model fertility-related career interruptions in order to quantify the "motherhood penalty" highlighted in the literature. Third, we embed taste-based discrimination—if there is any—in the gender differences in labor market behaviors in our framework, whereas Moser and Morchio (2019) allow firms to have a taste parameter for men relative to women and it accounts for most of the gap in Brazil (90%). Moser and Morchio (2019) find that mobility differences between men and women accounts for about 25% of the gap, whereas in our framework job-to-job mobility

[2] To the best of our knowledge, the only paper that considers the firms' channel in equilibrium is Bowlus (1997), which analyzes the static cross-sectional gender wage gap.

patterns between men and women are very similar and do not contribute to the gap, while the differences in separation rates account for a substantial share of it. These discrepancies have to do with the stark differences between the Brazilian and the U.S. labor markets. In particular, while men's separation rate is higher than women's in Brazil, it is the opposite in the U.S. for all education groups.

Finally, although our framework's wage determination differs from that of Bagger et al. (2019), their work is closely related to ours. Bagger et al. (2019) develop a search model with bilateral bargaining in which bilateral bargaining is exogenously fixed. Our paper uses a wage-posting framework, and departs from Bagger et al. (2019) in a few dimensions. First, we allow for the productivity distribution of firms to be gender specific, in line with the evidence in recent empirical literature that finds women to be more likely to work in lower-paying establishments than men (Albrecht et al. (2018), Goldin et al. (2017), Card, Cardoso, and Kline (2016)). Second, the focus of our paper is on the quantification of the endogenous responses of firms to gender differences in labor market behavior. Interestingly, both Bagger, Lesner, and Vejlin (2019) and our paper find a relatively small contribution of fertility-related career interruptions to the gap, even though Denmark and the U.S. have different family leave policies.[3] However, in contrast with Bagger, Lesner, and Vejlin (2019) who find that differences in worker productivity and in the returns to labor market experience drive most of the gap, we find a relatively weaker role of the human capital differences once market segregation and optimal wage-setting by the firms are taken into account.

Finally, Xiao (2019) explores the demand side of the gender wage gap when firms statistically discriminate and men and women differ in their preferences for amenities, fertility-related career interruptions and separation rates. Unlike our work, Xiao (2019) focuses on the differential sorting patterns of men and women across jobs of different productivity levels over the lifecycle, in particular, on the under-representation of women in the high-productivity positions. Interestingly, using linked employer-employee data for Finland, Xiao (2019) also finds that higher separation rates of women account for a substantial share of the life-cycle gap, especially when firms' responses to this relative employment instability are taken into account.

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

[3] Though in our estimates the channel is quantitatively more substantial than in Bagger, Lesner, and Vejlin (2019).

2 Data

We use 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.

For each week in the sample period, we know the employment status of a person, her occupation and industry, her wages, and how many hours she worked in each week. We can observe the transitions workers make across different jobs each worker had, however, we can only identify employers within each worker's employment history. Using this information we are able to reconstruct the (weekly) labour market histories of individuals since leaving full-time education, including the individua's transitions between employment and non-employment; transitions between jobs; actual and potential work experience; wages and hours worked, and birth of each child (if any).

We restrict our sample to non-black, non-Hispanic individuals in the first 15 years in the labor market and in order to have labor markets with comparable workers, we stratify the labor force by education level using the information on highest grade completed. We restrict our attention to individuals with 12 to 15 years of schooling—we refer to this as the group of "high school graduates",—and the group of those who have 16 to 20 years of schooling—which we refer to as the group of "college graduates".

Finally, in order to evaluate the impact of having children on life-cycle wages, we focus on people who had their first child after leaving school. These restrictions leave us 1,376 men and 1,331 women in the high-school graduates' group, and 653 men and 681 women in the group of college graduates.[4]

In terms of fertility, we know the date of birth of the child born to a respondent. Using this information we are able to reconstruct the detailed weekly labour market histories of individuals from 1979 to 2012. The main limitation we face with these data is that we do not directly observe parental leave take-up or job protection in the data. Thus, we infer fertility-related career interruptions from the worker's employment history by looking at each worker's employment status around the birth of her child. We assume that a worker is in a fertility-related career interruption if we observe the parent being non-employed[5] in any of the first 20 weeks of the child's life. Fertility-related interruptions last until the worker

[4] 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.

[5] We treat the states of unemployment and out-of-the-labor force as the same non-employment state (excluding fertility-related career interruptions, as described immediately).

is observed working for at least 4 consecutive weeks. If a worker was not working in the weeks preceding childbirth, these weeks are counted as fertility-related interruption up to 3 months before the date of birth. Not working before that counts as regular non-employment. We infer the leave being protected by the employer if the first employer she has after the maternity spell is the same as the last employer before that.

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.[6] The data in Waldfogel (1999) show that no more than 40% of employees in medium to large firms[7] (and no more than 20% in small firms[8])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.

In the model, workers are subject to a fertility shock that takes them into maternity leave. If the worker is employed, upon the maternity shock, she separates from her current job to take maternity leave, and her employer decides whether to provide her with job protection as we explain in Section 3.1.

To compute the turnover rates — job-finding, separation, and job-to-job moves, — we only use the transition events outside of fertility-related career interruptions . We do this so that the gender differences in the turnover are not, at least directly, related to fertility events, which we treat separately in the model.

[6] 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).

[7] These are firms with more than 100 employees.

[8] These are firms with less than 100 employees.

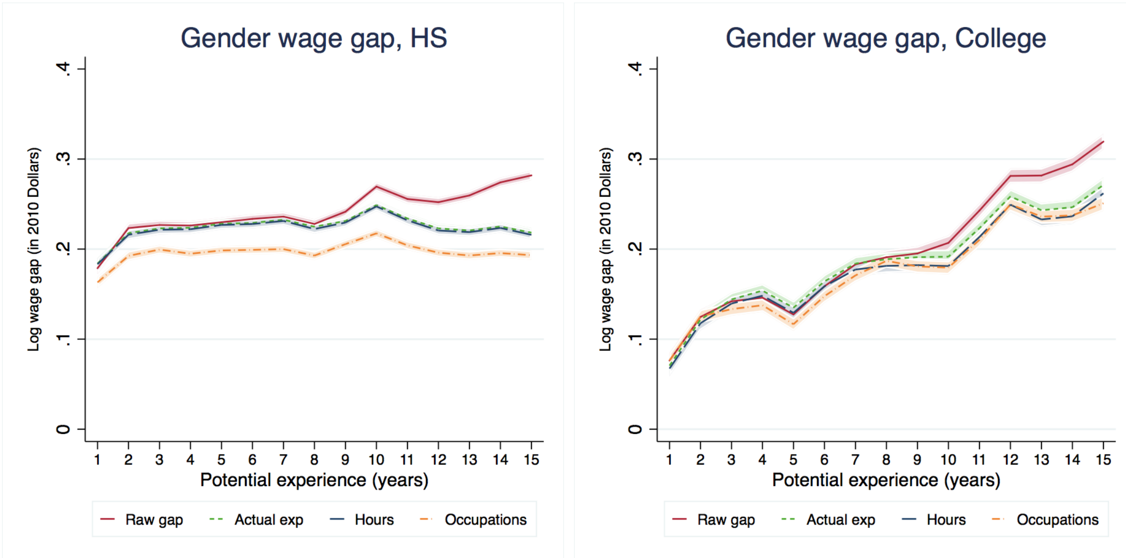


Figure 1: *Gender Wage Gap over the Life-Cycle*

Notes: The lines in the figures above represent the coefficients of male dummy in a series of regressions that include, sequentially: potential experience fixed effects, a quadratic in actual experience and 3-digit occupations. All the regressions control for year fixed effects.

2.1 Gender Wage Differences

This section provides descriptive evidence on the widening gap in earned wages between men and women, and gender differences in labor market turnover by education groups.

Substantial male and female wage differentials exist even at the beginning of workers' careers. The initial gap in log-wages is 0.18 for high-school graduates and 0.07 for college graduates in our sample. Fifteen years into a career, the gaps are 0.28 and 0.32, respectively, for the two education groups. The gap for more educated workers is smaller initially but its expansion is more pronounced than for the workers without a college degree. Controlling for occupation and hours worked has only a moderate impact on the size of the gap and its dynamics, as Figure 1 shows. Part of these widening wage gaps in Figure 1 might be attributed to different labor market behaviors of men and women. Table 1 presents some of these gender differences in the first 15 years of their working lives. Women tend to accumulate much less actual experience (a point highlighted by Erosa et al. (2016)). One of the reasons for this difference might be related to fertility—career interruptions around childbirth are very long for women relative to men, both when they return to their old job after childbirth and when they start working for a new employer.

The lower panel of Table 1 illustrates the differences in turnover rates across genders. For the less educated group, there are pronounced differences in the job-finding and job-to-job transition rates (women's rates are lower than men's by 24% and 19%, respectively). For

Table 1: Summary Statistics by Gender and Education

	HS Graduate		College Graduate +	
	Men	*Women*	*Men*	*Women*
Sample Size	1,376	1,331	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 ML	0.897	0.6943	0.9541	0.8058
Time spent in ML (months)				
Same job after ML	0.3151	1.9686	0.1449	1.8423
	(0.0337)	(0.1026)	(0.0081)	(0.2236)
Different job after ML	4.4867	16.9850	3.6523	14.8117
	(0.4876)	(1.0669)	(0.7253)	(2.0007)
Transition rates outside ML				
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

Note: This table reports the differences in turnover rates across genders by time that workers have been in the labor market for 15 years according to the 1979 National Longitudinal Survey of Youth (NLSY79).

the more educated group, the job-finding rate of women is lower than men's by 10%, and the separation rate of women is higher than that of men by striking 58%.

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 preferences, human capital accumulation technology, and search frictions are assumed to be gender and education specific. In what follows, we describe one such gender-education labor market. All gender $g \in \{m, f\}$ and skill superscripts $s \in \{\text{Highschool, College}\}$ are omitted to keep the notation as simple as possible.

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—yielding an overlapping generations structure where workers ages are distributed according to the exponential distribution.

Each worker enters the market with individual initial ability, ε—which represents human capital or productivity at the beginning of her career,—and is 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—following Burdett et al. (2016),—we interpret this increase as learning-by-doing. While unemployed, productivity stagnates. Hence, a type ε worker with actual experience x has productivity $y = \varepsilon e^{\rho^{gs} x}$.

Firms are risk-neutral and operate according to a constant returns to scale technology. They are heterogeneous in their technology parameter, p, drawn from the exogenous (and continuous) cumulative distribution function (CDF hereafter) $\Gamma(p)$ with support $\left[\underline{p}, \overline{p}\right]$. [9] At each instant, 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 flow profits. The flow productivity of the match (y, p) is yp, so that the 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 flow profits $\pi(p, z)$ from all the matches that will be formed at that instant.[10]

Let $F(z)$ denote the fraction of the firms that offer wage rates no greater than z. The offers' distribution is determined in equilibrium through firms' optimal choice of z.[11]

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 $\delta > 0$. 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. Third, workers are subject to fertility shock, upon which the worker goes out of the labor force into the maternity leave state (or ML).

Transitions into and out of ML are as follows. Workers may conceive a child in either employment or unemployment according to a Poisson process with rate γ_1. If the worker was employed when she has a child, she separates from her current job to take maternity leave, and her employer decides whether to provide her with job protection. We model this decision in a reduced-form and parsimonious way by assuming that there is a chance η that

[9] 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.

[10] 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. $w = \theta py$.

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

a job will be kept for a worker while she is on leave, and a chance $1-\eta$ that she will lose her job and will have to start searching again when she comes back to the labor market from maternity leave. If she receives job protection, she enters maternity 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. With the complementary probability if the worker is employed and with probability 1 if the worker is in unemployed, the worker does not get job protection and enters the state *NJP*, which is an unprotected maternity leave state and does not allow 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 while in the state *JP* she gets a second child, she losses the job protection provision and goes into the state *NJP*. So at each point in time, the worker, characterized upon joining the labor force by an individual initial ability $\varepsilon \sim A(\varepsilon)$ is either employed, unemployed, in *JP* or *NJP* for as long she is in the labor market.

Note that the differences in initial ability distributions may reflect limitations that some segments in the economy face in acquiring skills before joining the labor market, and not just innate abilities. Note also, that the gender differences in labor mobility or human capital accumulation parameters across genders may capture taste-based discrimination. For example, higher separation rates, or lower human capital accumulation rates of women could reflect, at least in part, taste-based discrimination of behalf of firms. As laid out in Section 3.3, firms and workers will take these parameters—regardless of the underlying mechanisms that characterize them—as given, when solving their optimization problems.

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), we have the following flow Bellman equation describing $U(y)$

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

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 flow Bellman equation describes the value function of the worker

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

The worker enjoys a flow payoff that is her wage zy, and the value of employment grows due to human capital accumulation. 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 firms are identical and human capital is both general and transferable across firms, $V(y,z)$ is increasing in z. Thus the employed move to any outside offer z' that is greater to the current wage rate. At rate γ_1 she has a child and with probability η she enter the job-protected maternity 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

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

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 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 maternity leave, with value $W^{NJP}(y)$ given by

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

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 C.1, the value functions take the following separable form,

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

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 $q(z)$. Then,

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

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

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

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

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

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

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

[12] 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.

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

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*

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

Given this characterization of optimal worker behavior, we now turn to optimal firm behavior.

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 set of employed workers m_E, *(ii)* the set of unemployed workers m_U, *(iii)* the set that is at home with the baby and has job protection m_{JP}, and *(iv)* the set that is at home with the baby who does not have job protection m_{NJP}. These steady-state measures have to satisfy the balance-flow conditions detailed in Appendix C.3.

Moreover, the measure of workers below a certain level of human capital x in 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; $N^{JP}(x)$, $N^{NJP}(x)$ the distributions of experience among workers with and without job protection respectively; $H(x,z)$ the joint distribution of experience and wage rates among employed workers; and $H^{JP}(x,z)$ the joint distribution of workers in maternity 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}, and m_{NJP} and the distributions $N(x)$, $N^{NJP}(x)$, and $H(x,z)$ are given in Appendix C.3.

3.3 Firms' Profits

Notice that offering a wage rate $z < z^R$ implies that the firm makes zero profit (the firm attracts no workers). Thus, in any market equilibrium we must have that $\underline{z} \geq z^R$, and this lower bound on the wage rates being offered in equilibrium, implies a lower bound on the productivity of firms that participate in the labor market which we derive below.

Since there is no discounting, steady state flow profits equal the hiring rate of the firm multiplied by the expected profit of each hire (Burdett et al. (2011)). As mentioned above, a firm with productivity p, posts a wage rate z that maximizes steady state flow profits. When a match between a firm with productivity $p \geq \underline{p}$ and a worker with human capital y is formed, the flow revenue is py and the wage contract is a fixed piece rate θ of this flow output, so that the wage of the worker is $w = \theta py$ and the flow profit of the firm from this match is $y(p - z)$, $z = \theta p$. Hence, the expected profits of the firm are 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 will stay with the firm, which we denote by $y^{acc}(z)$.

To characterize steady state flow profits $\pi(z, p)$ let us introduce four steady-state objects. Let m_U and m_E denote the measures of workers in employment and unemployment respectively. Let $N(x)$ denote the fraction of unemployed workers with experience no greater than x, and $H(x, z)$ the joint CDF describing the probability that an employed worker has experience no greater than x and wage rate no greater than z.[13]

First, note that the pool of potential hires consists of both employed and unemployed workers. $y^{init}(z)$ is thus defined by[14]

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

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 protected leave. Since the Poisson process governing fertility is memory-less, regardless of how many children a worker has had in the past, at each point

[13] Expressions for these steady-state objects are derived in Appendix 3.2.
[14] We provide details of the derivation in Appendix C.4.

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

$$y^{acc}(z) = \int_{\tau=0}^{\infty} \left[q(z)e^{-q(z)\tau} \int_0^{\tau} e^{\rho x} dx + \eta\gamma_1 e^{-q(z)\tau} e^{\rho\tau} \int_{\tau_1=0}^{\infty} \gamma_2 e^{-(\phi+\gamma_1+\gamma 2)\tau_1} y^{acc}(z) d\tau_1 \right] d\tau. \quad (6)$$

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. 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 maternity leave. The probability that she receives job protection upon a child shock after a match length of τ is $\eta\gamma_1 e^{-q(z)\tau}$. To ensure that she returns to the previous job, the event of returning should occur before retirement or an additional fertility shock—this happens with probability $\gamma_2 e^{-(\phi+\gamma)\tau_1}$ for any duration of maternity leave τ_1. When the worker returns, the expected events are exactly the same as at the beginning of the match because the Poisson process is memory-less. Thus, the expected accumulated human capital gain will again be $y^{acc}(z)$ (recall that the firm has zero discount rate).

Simplifying equation (6),[15] the firm's problem becomes,

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

Let us denote the optimal wage rate offer function by $\xi(p)$. We solve for the equilibrium in Appendix C.4 and provide a closed form equation defining defining policy function.

3.4 Definition of Market Equilibrium

The equilibrium is a tuple $\{z^R, m_E, m_U, m_{JP}, m_{NJP}, H(\cdot), N(\cdot), N^{JP}(\cdot), N^{NJP}(\cdot), H(\cdot,\cdot), H^{JP}(\cdot,\cdot), \xi(p)\}$ 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 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), so that $F(z) = F(\xi(p)) = \Gamma(p)$.

[15] Details of the derivation of this equation can be found in Appendix C.4.

4 Estimation Strategy

To bring the model to the data, for each gender, we parametrize the ability distribution $A(\varepsilon) \sim Weibull(\underline{\varepsilon}, \overline{\varepsilon}, \alpha_1, \alpha_2)$ and the productivity distribution $\Gamma(p) \sim Weibull(\underline{p}, \overline{p}, \kappa_1, \kappa_2)$. We consider the reference time period as a month, letting $\phi = 0.0033$ [16] and $r = 0.0041$.

There are thus 16 parameters to estimate for each gender: $\{\underline{p},\ \overline{p},\ \kappa_1,\ \kappa_2,\ \rho,\ \underline{\varepsilon},\ \overline{\varepsilon},\ \alpha_1,\ \alpha_2,\ \delta,\ \gamma_1,\ \gamma_2,\ \gamma_3,\ \lambda_e,\ \lambda_u, b\}$. We derive closed form expressions that allow us to recover $\delta, \gamma_1, \gamma_2, \gamma_3, \lambda_e, \lambda_u$ directly from the turnover and fertility data.[17] To estimate the remaining parameters, $\{\underline{p},\ \overline{p},\ \kappa_1,\ \kappa_2,\ \rho,\ \underline{\varepsilon},\ \overline{\varepsilon},\ \alpha_1,\ \alpha_2, b\}$, we use GMM and target a set of moments that speak to each of the parameters. The first set of moments we use are mean log-wage changes in job-to-job transitions at each of the first 10 years of actual experience. This set of moments is informative about the distribution of firms' productivities Γ, since wage changes upon job switches only depend on the wage ladder and not on the rate of human capital accumulation ρ or the individual initial ability ε. The second set of moments are mean log-wages in the same years, which help to pin down rho—the only source of wage growth beyond job-to-job transitions. Note that both job-to-job wage growth and mean log-wages contain information about the productivity at home, b, because it enters the reservation wage rate of the workers and is therefore directly related to the location of the lower rungs of the equilibrium wage ladder. The third set of moments consists of variance, skewness and kurtosis of the wage distribution for the same years. These moments reflect the shape of the wage distribution and are informative on both Γ and A. Finally, in the absence of firm-level data, we are unable to distinguish between two additive components of average wages - the average ability and the average wage offer. Therefore, we make an identifying assumption that the average ability of both genders is the same.

To sum up, our target moments are the first four moments of log-wage distribution (mean, variance skewness and kurtosis) together with the average job-to-job wage changes, each of them by year of actual experience, which we vary from 1 to 10—adding up to 50 moments. Let $f(X, \theta)$ denote the difference between the model implied target moments and their sample analogues, where N is the number of individuals in the sample.

The GMM estimator of the true $\{\underline{p}, \overline{p}, \kappa_1, \kappa_2, \rho, \underline{\varepsilon}, \overline{\varepsilon}, \alpha_1, \alpha_2, b\}$ is then

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

[16] Corresponding to an average of 25 years of prime-age career

[17] We provide details of the expressions that allow us to link data durations and probabilities to these parameters in Appendix D.1.

with W a symmetric, positive definite matrix. We adopt a two-stage efficient GMM procedure, as described in Appendix D.2.

Table 2 reports the estimated parameters for college-educated women. Estimates for college educated men are tabulated in Table 4 in Appendix E.2.

5 Model Fit and Parameter Estimates

We present our estimates for college-educated women in Table 2. Our estimates for college

Table 2: *Parameter Estimates for College Educated women*

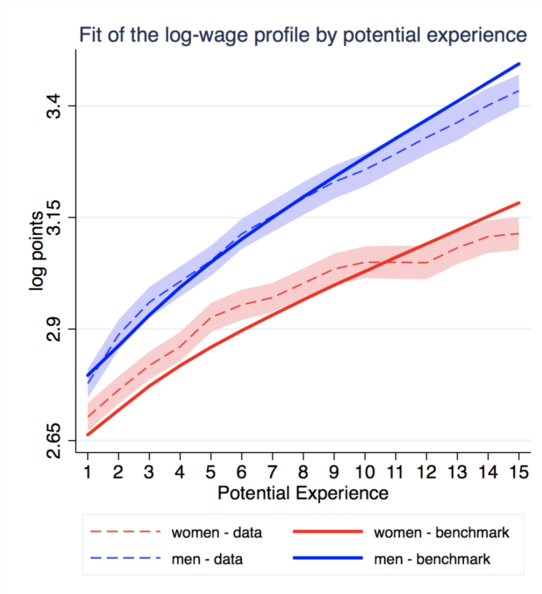
Estimates from data		Jointly estimated parameters	
δ	0.0224	$\underline{p}$	10.5413 (0.1433)
γ_1	0.0075	$\overline{p}$	56.5479 (1.3290)
γ_2	0.5253	κ_1	0.8024 (0.0396)
γ_3	0.0355	κ_2	30.7866 (2.0997)
λ_e	0.0344	ρ	0.0031 (0.0000)
λ_u	0.2012	$\underline{\varepsilon}$	0.5898 (0.0441)
η	0.8248	$\overline{\varepsilon}$	7.6516 (1.1036)
r	0.0041	α_1	2.6236 (0.1117)
ϕ	0.0021	α_2	4.1969 (0.4226)
		b	4.9439 (0.3535)

Note: This table reports the point estimates for college-educated women.

educated men are tabulated in Table 4 in Appendix E.2.

The model fits the log-wage profiles by actual experience remarkably well and we get the rest of the moments within the confidence bands. Summaries of the fit of the targeted moments by the model are presented in Figure 8 in Appendix E.1 and for men in Figure 9 in Appendix E.2. It is worthwhile noting that the target moments are computed by actual experience. Note that the transition rates determine how actual experience is being accumulated, so the log-wage profile by potential experience in Figure 2 shows the fit of both the jointly estimated parameters and the transition rates.

Figure 2: *Fit of the log-wage profile by years in the labor force*



Note: *The figures show the fit of the model-implied average log-wages by number of years in the labor market for college-educated workers*

5.1 Counterfactual policy exercises

In this section, we illustrate the mechanisms through which policies targeting the gap can impact life-cycle careers. In particular, we simulate the model when we eliminate gender differences in *i)* the probability to retain the job upon childbirth; *ii)* the arrival rate of offers in unemployment and *iii)* in employment; *iv)* the separation rate; and *v)* the human capital accumulation rate. For each of these changes, first, we highlight the differential impact on two additive components of life-cycle log-wage profiles: the profile of human capital log-levels and the profile of human capital log-prices — where the latter component reflects the process of climbing up the ladder, or the distribution of wage offers, which is determined in equilibrium. Second, for each of the changes, we simulate, on the one hand, a counterfactual scenario in which we keep the distributions of offers unchanged — we call this the *partial effect* of the policy and, on the other hand, a scenario where we allow for the distribution of offers to adjust — we call this the *full effect* of the policy.

Two main conclusions arise from this analysis. First, the endogenous adjustment of human capital prices is an important channel through which policies affect individual careers. Second, ignoring these endogenous adjustment leads to misleading conclusions regarding the impact of the policy, both quantitatively and qualitatively.

5.1.1 Lower separation rate for women

In Figure 3, we reduce the separation rate, δ,[18] of women by 36.8% to equalize it to the men's level.[19] Such a change would reduce the number of interruptions and allow for more accumulation of human capital. This effect is relatively small for an average woman as reflected in Figure 3a because separation events were already quite rare before the change[20] and a 36.8% lower separation rate does not starkly increase the average human capital accumulated by a woman. For a firm, however, the value of matches with all its female employees goes up, and the total effect on expected profits is substantial, the range of offers shifts up. It shifts up by less on the lower end, because the lower reservation rate of the workers pulls the lowest offers down — with more secure jobs, the relative value of employment increases, and workers are ready to accept lower wages. Figure 3b depicts the effect on the human capital price profile, which reflects a substantial increase in the top offers, a more moderate increase in the lower range of offers — relevant for inexperienced women — and a steeper curvature due to longer periods of uninterrupted on-the-job search and faster ascent up the prices ladder.

In terms of the gender wage gap, Figure 3c shows that the partial effect highly underestimates the full impact of the change. When the firms' wage-setting responses are ignored, the model predicts that the gap will decrease, but only for more experienced women, due mostly to gains from uninterrupted on-the-job search (because as we have seen in Figure 3a the human capital path is almost unaffected by the policy). However, when endogenous firms' wage offers are allowed to adjust — i.e. when we consider the full effect of the policy, — there is a drastic reduction of the gap of 12.5 log-points (or 41.77%) on average over the first 15 years of a career. Had we ignored these equilibrium responses, we would have missed over 80% of the policy impact, especially for women at the beginning of their careers.

5.1.2 Increased arrival rate of offers for unemployed women

Figure 4 shows the effect of increasing the job-finding rate in unemployment, λ_u, by 16.4% to equalize it to the men's rate.[21] This change would shorten the unemployment spells of women, increasing the average human capital they can accumulate at each level of potential

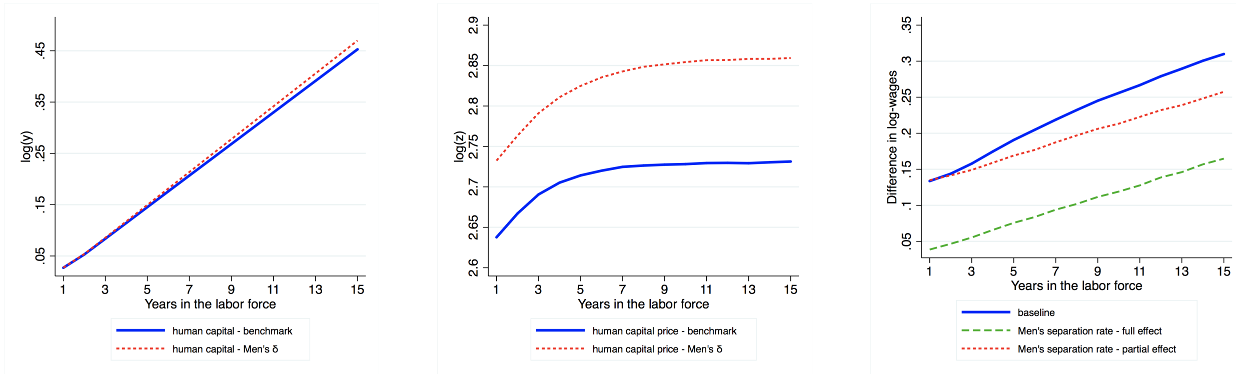
[18] Though this separation rate considers only separations outside of the parental leave spell, it can potentially reflect that family-related responsibilities that are mostly carried by women.

[19] This hypothetical change could be achieved through a policy that helps women to cope with family related responsibilities such as better childcare provisions or higher flexibility in hours of a job.

[20] Recall that the probability that an employed college-educated woman is unemployed next month is 2.25% as shown in Table 1 in Section 2.

[21] We could think of increasing the job-finding rate in unemployment through a policy that helps unemployed women to search more efficiently.

Figure 3: *Lower separation rate*



(a) *Average human capital* ***(b)*** *Average human capital price* ***(c)*** *The gender wage gap*

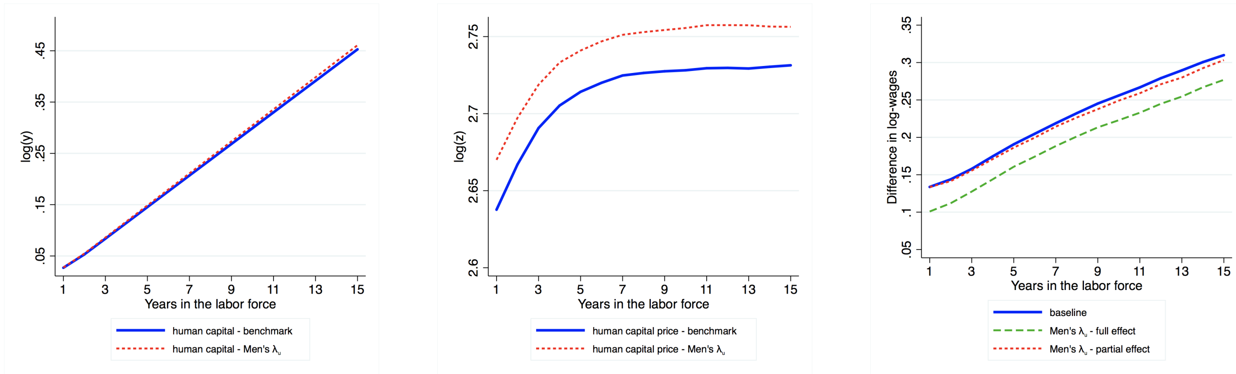
Note: *The figure shows the effect of a 36.8% decrease in the separation rate, δ, to equalize it to the men's level. Panel (a) shows the effect on human capital profile, Panel (b) shows the effect on the average wage rate profile; in Panel(c), the baseline gap in log-wages between men and women is depicted with a solid blue line, the dotted red line shows the partial effect of a change in the parameter whereas the dashed green line shows the total effect that includes equilibrium responses of the firms.*

experience. This effect on human capital levels is cumulative and thus more pronounced at longer horizons as Figure 4a shows. However, the effect is numerically small since unemployment itself is a relatively sporadic event[22] in the life of an average woman. For the firms, a higher arrival rate of offers in unemployment means that a given offer attracts more workers from unemployment (see equation (7) in Section 3), increasing the profit rate, which is passed on to the workers in the form of higher wage offers. The relative value of unemployment goes up — since unemployed search is more efficient, — and the reservation rate increases, raising the wage offers at the lower end of the distribution by more than at the higher end and providing an additional wage rate boost for inexperienced women. Given a better menu of offers, the profile of earned human capital prices shifts up, as can be seen in Figure 4b.

As with the coverage policy in Section 5.1.4, the price effect is stronger than the effect on the human capital levels. In Figure 4c we clearly see that if the optimal wage-setting decisions of the firms are ignored, the predicted effect of the policy on the gap — the partial effect — would be very small and only visible later in a career, whereas the full effect would be a non-negligible reduction of the gap by 3.1 log-points (or 19.9%) in the first 5 years of potential experience and by 3.4 log-points (which corresponds to 11.8% as the gap increases) in years 11-15.

[22] The probability that an employed college-educated woman is unemployed next month is 2.25% (see Table 1 in Section 2).

Figure 4: *Higher offers arrival rate in unemployment*



(a) *Average human capital* ***(b)*** *Average human capital price* ***(c)*** *The gender wage gap*

Note: *The figure shows the effect of a 16.4% increase to equalize it to the men's arrival rate of offers in unemployment,* λ_u*. Panel (a) shows the effect on human capital profile, Panel (b) shows the effect on the average wage rate profile; in Panel(c), the baseline gap in log-wages between men and women is depicted with a solid blue line, the dotted red line shows the partial effect of a change in the parameter whereas the dashed green line shows the total effect that includes equilibrium responses of the firms.*

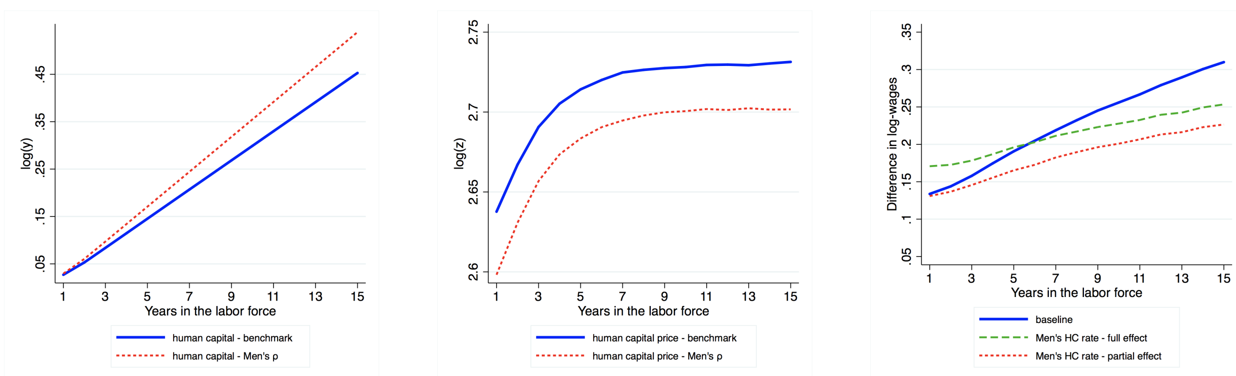
We do a similar exercise to quantify the effects of equalizing the job finding rate in employment, λ_e, to the level of men, which implies a decrease of 7.9%, in Appendix E.3.1. Under this change, the gap increases by 0.7 log-points (or 7.2%) at the onset of workers' careers and by 1.5 log-points (which corresponds to 5.2% as the gap increases) in years 11-15.

5.1.3 Higher human capital accumulation rate for women

In Figure 5 we consider a 19.6% increase in women's human capital accumulation speed, equalizing their technology to the men's level. As a direct consequence, female workers become more productive and their human capital paths become significantly steeper, as reflected in Figure 5a. The impact on the human capital prices is not straightforward: the equilibrium wage ladder for females actually shifts *down*. The reason being, on the one hand, that more productive matches are more valuable, shifting the firms' offers up. On the other hand, that workers value employment more relative to unemployment because the lifetime benefits of additional human capital, which is general and does not depreciate, are high. As a result, workers are willing to accept lower reservation wage rates in order to access this efficient learning-by-doing technology. In equilibrium, both these endogenous effects — firms ready to pay higher wages and workers ready to accept much lower wages — interact and the lowest offer goes down and the highest offer goes up, but just a little bit relative to the reduction at the lower end. Overall, the menu of human capital prices deteriorates for women, resulting in the downward shift of the prices profile over a career, as in Figure 5b.

If we ignore the equilibrium responses of the firms, we get that the gender wage gap reduces significantly, especially towards year 15 where the cumulative effect of actual experience is the highest — as reflected by the red dashed line in Figure 5c. However, the *total effect* is more nuanced and incorporates the changes in the human capital prices set by the firms. The green dashed line shows the *total effect* and we see that the gap actually expands by 2.1 log-points (or 14.1%) for inexperienced women in years 1-5 of a career — they have not yet reaped the benefits of higher human capital accumulation, but are already exposed to a menu of lower human capital prices. For women later in a career, the gap shrinks by 0.045 (or 15.7%) on average in years 11-15, because the benefits of additional human capital stock outweigh the costs of lower human capital prices. The partial effect fails to capture the nuanced equilibrium responses outlined above and thus would mislead the policy analysis.

Figure 5: *Higher human capital accumulation rate*



(a) *Average human capital* ***(b)*** *Average human capital price* ***(c)*** *The gender wage gap*

Note: *The figure shows the effect of a 19.6% increase in the human capital accumulation rate ρ to equalize the parameter to the men's level. Panel (a) shows the effect on human capital profile, Panel (b) shows the effect on the average wage rate profile; in Panel(c), the baseline gap in log-wages between men and women is depicted with a solid blue line, the dotted red line shows the partial effect of a change in the parameter whereas the dashed green line shows the total effect that includes equilibrium responses of the firms.*

5.1.4 Increased protected maternity leave coverage

In Figure 6, we examine the effect of increasing the incidence of job-protected maternity leave for women to the level of men (16.2% increase in η), meaning that more women can come back to their old jobs after having a child and do not have to spend time searching for a new position. Such a policy would have virtually no effect on the human capital profile of an average woman as Figure 6a shows; this is because the fertility events are rare.[23] However, for each firm, the higher incidence of women who continue their jobs after childbirth implies that average match duration increases. Now, firms have a longer horizon over which to reap the benefits of women's growing human capital, increasing the value of the match. Part of this increase is passed on to women in the form of higher wage offers. This means that women now sample human capital prices from a better distribution, which is reflected in the upward shift of the wage rate profile in Figure 6b. Note that the increase in the price profile for younger women is less pronounced than for more experienced women. This is due to a subtle equilibrium effect: the higher incidence of job protection makes employment relatively more valuable than unemployment, bringing the reservation wage rate down. In equilibrium, the lowest offer balances the willingness of the workers to accept lower wages and the willingness of the firms to pay a higher rate. As a result, the wage offers at the lower end of the distribution increase less than the offers at the higher end. This means that younger women — who usually start from the lower rungs of the wage ladder — will experience a weaker increase in the price they get for their human capital than women later in a career.

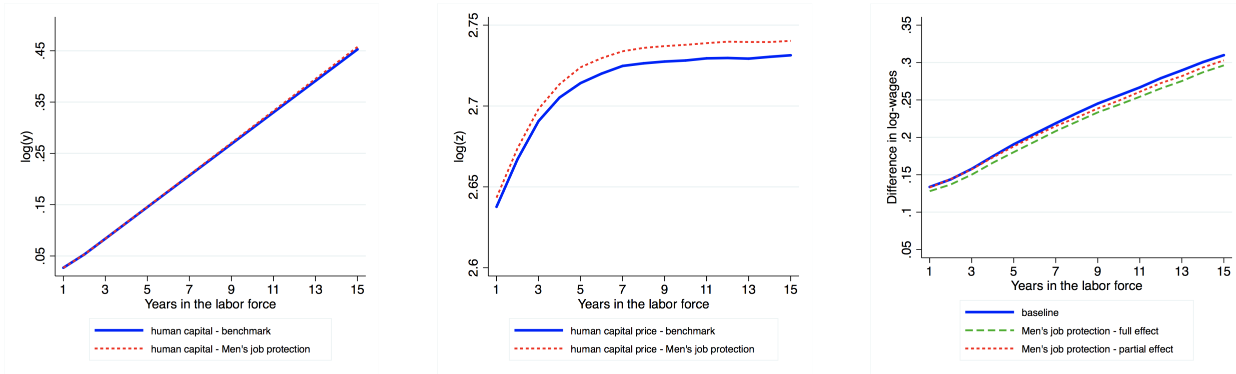
Though not big quantitatively, the impact of the policy on *human capital prices* is stronger than its impact on *human capital levels*. This point is further illustrated in Figure 6c, where we show that when the distribution of offers is fixed, the policy has virtually no impact on the gender wage gap — i.e. the partial effect is very small. Only later in life, one can see some gains from the additional time spent in employment. Once the response of the firms is included, however, the effect is already felt at the beginning of a career, since young women also enjoy a slightly better menu of offers. In particular, the total effect would reduce the gap by 0.8 log-points (or 4.9%) on average in the first 5 years of a career, and by 1.4 log-points (or 4.7%) in years 11-15, where most of gains are due to the improvements in human capital prices which are set endogenously by the firms.

5.2 Quantifying the components of the 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 perform a decomposition of the gap into three additive parts, reflecting differences in human capital level, differences in wage rates due to jobs segregation, and differences in wage rates due to statistical discrimination. Let us denote with $w^d = y^d z^d$ the wages received by workers of gender $d \in \{f, m\}$ and let Γ^{men}

[23] Recall that college educated women have 1.3725 children upon 15 years of being in the labor force (see Table 1 in Section 2).

Figure 6: *More maternity leaves with job-protection*



(a) *Average human capital* ***(b)*** *Average human capital price* ***(c)*** *The gender wage gap*

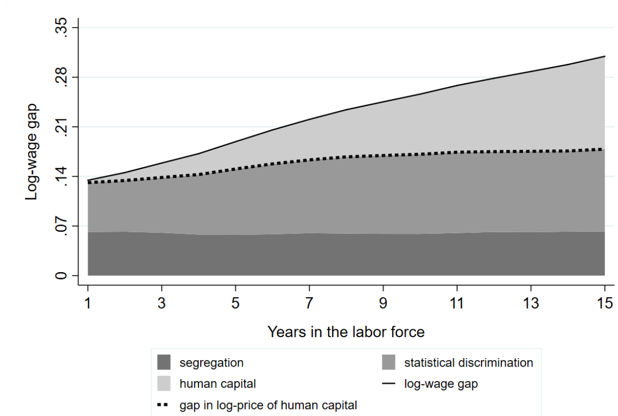
Note: *The figure shows the effect of equalizing the parameter η — that governs the availability of the maternity leave with job protection, — to the level of men; a 16.2% increase. Panel (a) shows the effect on human capital profile, Panel (b) shows the effect on the average wage rate profile; in Panel(c), the baseline gap in log-wages between men and women is depicted with a solid blue line, the dotted red line shows the partial effect of a change in the parameter whereas the dashed green line shows the total effect that includes equilibrium responses of the firms.*

denote the distribution of firm productivities in the men's labor market.

$$\begin{aligned} gap &= \log(w^m) - \log(w^f) \\ &= \log(y^m) + \log(z^m) - \log(y^f) - \log(z^f) \\ &= \underbrace{\log(y^m) - \log(y^f)}_{\text{gap in human capital}} + \underbrace{\log(z^f)\ |_{\Gamma^{men}} - \log(z^f)}_{\text{jobs segregation}} + \underbrace{\log(z^m) - \log(z^f)\ |_{\Gamma^{men}}}_{\text{statistical discrimination}} \end{aligned} \tag{8}$$

The first component in **??** above reflects the differences in human capital *levels* accumulated by men and women over their careers. The second and the third components together represent the differences in the *prices* that men and women receive in the labor market for their units of human capital, where we distinguish between *(i)* the effect of job segregation—the gap in wage rates that is due to the fact that women don't work in the same jobs as men, and *(ii)* the effect of statistical discrimination—the gap in wage rates that arises due to differential wage-setting by the firms, even if women were employed in exactly the same jobs as men. Figure 7 illustrates this decomposition over the life-cycle where the solid black line represents the total gap, and the gray areas below it represent the three additive components outlined above. On average, over the first 15 years of a career, 45% of the gap is explained by the differential wage setting by the firms, in response to gender differences in turnover and human capital process. The segregation of jobs accounts for 28% of the gap and the remaining 26% is due to differences in human capital profiles. The latter component is cumulative, it more than doubles towards the end of our horizon, when it accounts for 42% of the gap. This gap in human capital levels is the main driver of the total gap expansion, explaining 72% of it, and the remaining 28% of the expansion are due to the fact that men and women climb different wage ladders, and over time women increasingly fall behind men in terms of earned human capital price. This divergence is entirely explained by the statistical discrimination mechanism which compresses women's wage rates especially at the higher rungs of the ladder. The flow output in these high-productivity jobs is higher—both because the firms themselves are more productive, and because workers employed in these jobs tend to be more experienced. Therefore, match stability is especially valuable for these firms, and they will discount the wage rates of high-turnover group more.

Figure 7: *Log wage gap - contribution of human capital, market segregation and statistical discrimination*



Note: *The figure shows the total log wage gap (black solid line) and its components - the gap due to segregation (dark gray area), the gap due to statistical discrimination (gray area) and the gap due to human capital differences (light gray area). The dashed line represents the gap due to human capital prices.*

As highlighted before, our model allows men and women to differ along a number of broad dimensions — fertility shocks, transition rates, human capital technology, and firm productivity. To quantify the contribution of each dimension to the overall gap, we perform a series of counterfactual exercises by successively giving women the structural parameters of men and simulating the model each time to assess the predicted gap under the new set of parameters.

The effects of each of the four channels in isolation are shown in columns II-V of Table 3. Gender differences in mobility explain a large portion of the wage gap: equalizing the transition parameters between men and women reduces the wage gap by 61.2% on average over the life-cycle. Gender segregation across firms of different productivities is also an important factor and accounts for 26.5% of the average wage gap. Equalizing fertility-related parameters and human capital technology between men and women reduces the wage gap by 10% and 2.6%, respectively. In terms of the gap expansion, equalizing the human capital accumulation rate seems the most effective policy: it reduces the gap expansion by almost a half, by tilting women's wage profiles upwards towards the end of the career, as illustrated in Section 5.1.

Table 3: *Closing the gap between men and women by equalizing their parameters*

Equalized	I	II	III	IV	V	VI	VII	VIII	IX	X
–	baseline									
fertility		✔				✔	✔		✔	✔
transitions			✔			✔		✔	✔	✔
$\Gamma(p)$				✔					✔	✔
ρ					✔		✔	✔		✔
Predicted										
average gap	22.6	20.3	8.8	16.6	21.3	6.3	18.8	5.8	−0.6	−3.8
gap opening	17.6	16.0	14.1	17.6	8.7	12.1	6.4	4.5	1.18	1.7
$\frac{\text{combined effect}}{\sum \text{separate effects}}$						1.01	1.06	1.11	1.05	1.13

Note: The table reports the gender wage gap in log-points when different sets of parameters are equalized. Column I shows the gap predicted by the model at baseline values; column II equalizes the fertility parameters of women to the level of men; column III equalizes the labor mobility parameters to the level of men; column IV equalizes the distribution of firms' productivities and column V equalizes the human capital accumulation rate. Then, in columns VI–VIII we additively equalize the same sets of parameters, one by one. Column VIII shows the predicted gap when all but one of the women's parameters have been equalized to the level of men, namely, the flow value of non-employment, b. Equalizing b closes the gap completely. The last row of the column computes the ratio of the gap reduction under combined policy to the sum of the gap reductions under the components of the policy.

As columns VI-X show, there are complementarities between the channels, especially between human capital accumulation rate and transition rates. The combined effect of these two channels is 11% higher than the sum of the separate effects. With a higher human capital accumulation rate, an improvement in the transition rates of women brings about a stronger reduction of the gap (column VIII *vs* column V) than the same improvement when ρ is low (column III *vs* column I). When human capital accumulates faster, any given increase in actual experience due to more stable employment increases average human capital stock by more. At the same time, firms value match stability more when employees' human capital grows faster and respond with a better distribution of offers.[24] This complementarity is quantitatively weaker when the human capital accumulation rate is equalized in conjunction with the fertility channel (column VII), because the latter does not lead to a substantial

[24] The intuition also works vice versa — with more stable employment, the benefits of a higher human capital accumulation rate will be more salient for both firms and workers.

increase in the accumulation of actual experience nor in the expected match durations.

As shown in column X of Table 3, the higher human capital accumulation rate also boosts the efficiency of the rest of the channels combined — and this policy leads to a 13% stronger reduction in the gap than the sum of separate policies implies.

6 Concluding Remarks

This paper analyzes the differential wage growth between men and women 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 human capital prices channel—wage rates set by the firms for men and women—are a major source of the gender wage disparities. We also find that these endogenous wage-setting decisions are an important transmission channel through which policies impact individual labor market outcomes. Counterfactual exercises demonstrate that disregarding these effects leads to erroneous conclusions about the impact of various policies that target the gap, especially with respect to workers at the beginning of their careers.

Fertility-related career interruptions have a non-negligible effect on the life-cycle gap. The model predicts that if women had the same patterns of fertility-related interruptions as men, the gap would by approximately 10% lower at all levels of experience and it will widen less over the life-cycle. However, the most effective policy to narrow the gap in log-wages would be to equalize the transition rates across genders and to reduce the jobs segregation by gender. Differences in transition parameters (job-finding and separation rates) account for 63.8% of the gap in years 1-15 of a career. The differences in separation rates are particularly important. In fact, eliminating the 58% difference in the separation rates, and encouraging women to work in exactly the same firms as men, would be enough to eliminate the entire gender wage gap in the first 15 years of potential experience, according to the model.

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 attempts to take a step in that direction.

The results of the numerical analysis highlight the importance of the gender differences in separation rates and the differences in the types of jobs employing men and women. This warrants a more detailed analysis of these two phenomena. In fact, the recent literature recognizes the importance of firm heterogeneity for the gender wage gap and its life-cycle dynamics (Barth, Kerr, and Olivetti (2017), Card, Cardoso, and Kline (2016)). The detailed analysis of the job-separation decisions of men and women is still an open area of research.

Finally, there are a number of potentially endogenous margins that are fixed in our analysis, such as the decision to promote, to provide job-protected maternity leave, to hire or to lay a worker off. Endogenizing these margins, as well as allowing for more endogeneity on the workers' side, such as investment in human capital or timing of childbirth, is left for future research.

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A Appendix

B Sample Restrictions

NLSY79 oversamples minorities and military personnels. We only use the “Non-black, non-Hispanic” sample, and also drop the poor and military samples.

We define potential experience starting from the year the person leaves full-time education, that is, potential experience = age - years_of_schooling - 6.

We focus on the first 15 years of potential experience. We drop people who had children before leaving school, and drop those who have not worked at all in the 15 years after school.

B.1 Education

We focus on two education groups - high-school graduates (12 to 15 years of schooling) and college graduates (16 to 20 years of schooling). The variable educated takes on values 0 or 1, respectively.

B.2 Price index

We take the quarterly Consumer Price Index, and evenly spread the change in prices over weeks of each given quarter.

B.3 Employment status

We consider a person working in a particular week (working=1) if he/she is associated with an employer in this week, and the wage data is not missing. We consider a person not working (working=0) if he/she is either unemployed, or OLF (the model does not distinguish between these two states), or “associated with employer, but dates missing”. The variable "working" takes on the value "missing" if a person is in the military, or when no info is given regarding the employment status.

B.4 Transitions

For each week of potential experience we compute the number of people employed in this week (working=1) , the number of people nonnemployed (working=0), and the number of those who make transitions, from current week to the next week. We consider three types of transitions: job-to-job, non-employment to employment, and employment-to-nonemployment.

Then we divide the number of people making a transition by the corresponding denominator (employed or unemployed) in each week, to get weekly transition rates for each week. Then we convert the weekly transition rates x_w into the monthly rates x_m according to the formula:

$$x_m = 1 - (1 - x_{m,1}) * (1 - x_{m,2}) * (1 - x_{m,3}) * (1 - x_{m,4}) \tag{9}$$

where $x_{m,i}$ is the weekly transition rate in week i of month m 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 the Estimation section, the model produces a closed-form solution for the job-to-job transition rate at each level of actual experience. The counterpart in the data is computed by weeks and then months of actual experience by the same methodology as above, and then averaged over 10 years of actual experience.

B.5 Maternity Leave variables

We assume that a woman is on ML if we observe her non-employed in any of the first 20 weeks of her child's life. The fertility-related career interruption lasts till a woman is observed working for at least 4 consecutive weeks. The career interruption is interpreted as maternity leave if a woman comes back to her previous employer and as maternity leave *plus* unemployed search if a woman had a kid in non-employment or is observed coming back to work for another employer. If a woman was observed non-working in the weeks preceding birth, these weeks are counted as ML as well up to 13 weeks (three months) before the birth of the child. Beyond that time, a woman is considered non-employed. Since we use the duration of fertility-related career interruptions in our identification, we stretch any such spells beyond the 15 years window, and drop any individual for whom we do not observe the spell ending before 2013 (the last period in our sample).

C Model Appendix

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

C.1 Linearity of the Value Functions

The productivity y of a woman initial ability $\varepsilon \sim A(\varepsilon)$, can be expressed as a product of two components,

$$y = \varepsilon e^{\rho x}.$$

Therefore, when this woman is employed,

$$\frac{\partial y}{\partial t} = \rho y$$

The dynamic component in the value function of employed workers is given by

$$\begin{aligned} \frac{\partial V\left(y,z\right)}{\partial t} &= \frac{\partial V\left(y,z\right)}{\partial y}\frac{\partial y}{\partial t} \\ &= \frac{\partial V\left(y,z\right)}{\partial y}\rho y. \end{aligned} \tag{10}$$

An important feature of equation (10) is that the dynamic component is proportional to woman'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

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

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.

C.2 Derivations: Worker's Side

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

Proposition 2. *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*

$$\frac{d\alpha^E(z)}{dz} = \frac{1}{r + q(z) - \rho - \frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}}.\text{[25]} \tag{11}$$

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

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

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

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

$$\zeta_1\alpha^U = b + \frac{\gamma_1}{r+\phi+\gamma_3} b^{out} + \lambda_u \int_{z^R}^{\overline{z}} \frac{\overline{F}(z)}{r + q(z) - \rho - \frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma 2}}\, dz. \tag{15}$$

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*

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

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

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

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

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

---

[25] 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.

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

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, $\overline{z}$.

Note that any unemployed woman 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,

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

(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,

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

Simplifying and using (17),

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

C.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
$\lambda_u\, m_U\, N(x) + \gamma_2\, m_{JP}\, N^{JP}(x) = (\phi + \delta + \gamma_1)\, m_E\, H(x) + m_E\, \frac{d\,H(x)}{dx},$

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

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

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

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

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

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 women at home 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 women at home 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 women with job protection finishing maternity leave and coming back to their previous jobs, $m_{JP}N^{JP}(x)\gamma_2 dt$, and unemployed women 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 women being fired, retiring, and getting a child shock, $m_E H(x)\,(\phi+\delta+\gamma_1)\,dt$, and women 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,

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

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

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

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

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 women at home 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)*. $\square$

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

Proof. The inflow into the pool of employed women 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 $m_E\left(H(x,z)-H(x-dt,z)\right)$. 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

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

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,

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

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)*. $\square$

C.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

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

and

$$\int_0^\infty e^{\rho x'}\frac{\partial H(x',z)}{\partial x}dx = \frac{m_U}{m_E}\cdot\frac{\lambda_u F(z)}{q(z)-\frac{\eta\gamma_1\gamma_2}{\phi+\gamma_1+\gamma_2}-\rho}\left[1+\frac{n_2\rho}{(\zeta_4-\rho)}\right],$$ [26]

Therefore,

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

[26] 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 $y^{init}(z) = \zeta_6/M(z)$ and let us now derive in detail the expression (**??**) for $y^{acc}(z)$.

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.[27] 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 woman 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 woman will come back to her previous job in period τ' is given by[28]

[27] 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

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

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

[28] 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 ML. 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 $\tau' \in \mathbb{R}^+$.

$P_3(\tau') = \gamma_2 e^{-\gamma_2 \tau'} e^{-(\phi+\gamma_1)\tau'}$. Thus yielding the following recursive expression for $y^{acc}(z)$,

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

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

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

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

Recall that we denote the optimal wage rate offer function by $\xi(p)$. In equilibrium, for any $z \in \left[z^R, \overline{z}\right]$, $F(z) = F(\xi(p)) = \Gamma(p)$. 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

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

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

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

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*,*

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

with $\zeta_7=(\lambda_u-\lambda_e)(r+\phi+\gamma_1+\gamma_3)-\frac{\rho(r+\phi+\gamma_3)\lambda_u}{r+\phi}+\frac{(\gamma_3-\gamma_2)\eta\lambda_u\gamma_1}{r+\phi+\gamma_1+\gamma_2}$ *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: $\int_{\phi(a)}^{\phi(b)}f(x)dx=\int_a^b f(\phi(t))\phi'(t)dt$,

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

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

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

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

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

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),

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

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

□

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

$$
\begin{aligned}
&(r+\phi)\left(\frac{r+\phi+\gamma_3+\gamma_1}{r+\phi+\gamma_3}\right)\frac{\lambda_u z^R-\lambda_e b+\frac{\gamma_1\lambda\_u\eta b^{out}}{r+\phi+\gamma_1+\gamma_2}+\left[(\lambda_u-\lambda_e)-\frac{\eta\lambda_u(r+\phi+\gamma_2)}{r+\phi+\gamma_1+\gamma_2}\right]\frac{\gamma_1 b^{out}}{r+\phi+\gamma_3}}{(\lambda_u-\lambda_e)\left(r+\phi+\gamma_1-\frac{\gamma_1\gamma_3}{r+\phi+\gamma_3}\right)-\rho\lambda_u+\frac{(r+\phi)(\gamma_3-\gamma_2)}{r+\phi+\gamma_3}\frac{\eta\lambda_u\gamma_1}{r+\phi+\gamma_1+\gamma_2}} \\
&=b+\frac{\gamma_1 b^{out}}{r+\phi+\gamma_3} \\
&+\lambda_u\left(\frac{\left(\underline{p}-z^R\right)\zeta_6}{\phi+\delta+\gamma_1+\lambda_e-\rho-\frac{\gamma_1\gamma_2\eta}{\phi+\gamma_1+\gamma_2+c}}\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\xi_1'(x)dx\right. \\
&\left.+\int_{\underline{p}}^{\overline{p}}\frac{(1-\Gamma(x))}{\left(q(x)+r-\rho-\frac{\eta\gamma_1\gamma_2}{r+\phi+\gamma_1+\gamma_2}\right)}\xi_2'(x)dx\right).
\end{aligned}
\tag{29}
$$

(29) 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).

D Details of Estimation

D.1 Estimation directly from the Data

First, the average number of children that a woman 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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Note that z enters $D_{EtoE}(z)$ only through $F(z)$ — i.e. we could re-write $D_{EtoE}(z)$ as a function $\tilde{D}_{EtoE}(F(z))$. The key feature that allows us to obtain an expression of λ_e that has a data-counterpart is that z enters $H(z|x)$ only through $F(z)$ as well. Thus $dH(z|x)$ is a function of parameters, $F(z)$ and it is proportional to $f(z)$, which allows for the integral to be solved for and does not depend on $F(z)$.[29] 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

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

where $H(x) = 1-e^{-Rx}$. Thus

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

[29] 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 $\underline{z}$.

$$
- \frac{1}{(q(z)-\omega)^2} - \frac{e^{-R}}{(q(z)-\omega-R)^2}\Bigg)\Bigg] f(z)dz
$$

because $q'(z) = -\lambda_e f(z)$. To algebraically show that (34) does not depend on $F(z)$, following Hornstein et al. (2011), consider the change of variable given by $t = F(z)$ so that $(F^{-1})'(t) = \frac{1}{f(z)}$. It follows that

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

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

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

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

with

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

Therefore,

$$
D_{EtoE}|x = \int_{\underline{z}}^{\overline{z}} \frac{\frac{\lambda_e\cdot(1-F(z))}{q(z)}\cdot\left(1-e^{-q(z)}\right)F'(z)}{e^{-(q(\overline{z})-\omega)\cdot x} + \frac{n_2\cdot\left(R\cdot e^{-R\cdot x}-(q(\overline{z})-\omega)e^{-(q(\overline{z})-\omega)\cdot x}\right)}{q(\overline{z})-\omega-R}}
$$

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

which does not depend on F.

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

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 maternity leaves, average job-to-job transition rate and the share of women coming back to their old employer after maternity leave. We solve the system and with parameters in hand, proceed to the second stage of the estimation.

D.2 Joint estimation via GMM

We adopt a two-stage efficient GMM procedure, where in the first step each of the 50 moments is weighted by the inverse of its variance in the data. In the second step, the efficient weighting matrix is the inverse of the variance-covariance matrix of the set of moments we target, evaluated at the point estimate from the first step, $\hat{\theta}_1$. Note however, that our sample size is relatively small — $N = 681$ for women and $N = 653$ for men, — and that some of our moments will be missing for many individuals, precluding the required computation of covariances of the moments across individuals — for example, job-to-job transitions are very scarce and so the job-to-job wage changes at some levels of actual experience will be missing for all the workers that did not do a job-to-job transition at that level of experience. To deal with this issue, we resort to bootstrap to compute the efficient weighting matrix.First, we re-sample our data with replacement B times. Then, for each sample $b = 1, \ldots, B$ of size N, we compute the vector of moment conditions as the average of the individual-level moments, evaluated at $\hat{\theta}_1$. Let $g(X^b, \hat{\theta}_1) = \frac{1}{N}\sum_{i=1}^{N} f(X_i^b, \hat{\theta}_1)$ denote the 50×1 vector of moments in a bootstrapped sample b. Let $G(X, \beta)$ be the $50 \times B$ matrix formed by the vectors $g(X^b, \hat{\theta}_1)$, $b = 1, \ldots, B$.

I.e.

$$G(X, \beta) = \left(g(X^1, \hat{\theta}_1), \ldots, g(X^B, \hat{\theta}_1)\right),$$

where $[G(X, \beta)]_{i,j}$ corresponds to the i-th target moment of the j-th bootstrap sample.

Let $\widehat{\Omega}$ be a 50×50 matrix whose (m, ℓ) entry is given by

$$\widehat{\Omega}_{m\ell} = \frac{1}{B}\sum_{b=1}^{B} g_m(X^b, \hat{\theta}_1) g_\ell(X^b, \hat{\theta}_1) \xrightarrow{p} \mathbb{E}\left(g_m(X, \hat{\theta}_1) g_\ell(X, \hat{\theta}_1)\right).$$

Where $g_m(X^b, \hat{\theta}_1)$ and $g_\ell(X^b, \hat{\theta}_1)$ are the m-th and the ℓ-th elements of a vector $g(X^b, \hat{\theta}_1)$. Note that:

$$\begin{aligned}
\mathbb{E}\left(g_m(X, \hat{\theta}_1) g_\ell(X, \hat{\theta}_1)\right) &= \mathbb{E}\left(\frac{1}{N^2}\left(\sum_{i=1}^{N} f_m(X_i^b, \hat{\theta}_1)\right)\left(\sum_{j=1}^{N} f_\ell(X_j^b, \hat{\theta}_1)\right)\right) \\
&= \mathbb{E}\left(\frac{1}{N^2}\left(\sum_{i=1}^{N} f_m(X_i^b, \hat{\theta}_1) f_\ell(X_i^b, \hat{\theta}_1) + \sum_{i=1}^{N}\sum_{j \neq i} f_m(X_i^b, \hat{\theta}_1) f_\ell(X_j^b, \hat{\theta}_1)\right)\right) \\
&= \mathbb{E}\left(\frac{1}{N^2}\sum_{i=1}^{N} f_m(X_i^b, \hat{\theta}_1) f_\ell(X_i^b, \hat{\theta}_1)\right).
\end{aligned}$$

Where the last equality follows from the fact that the moments are uncorrelated across individuals. Thus

$$\widehat{\Omega}_{m\ell} \xrightarrow{p} \frac{1}{N}\mathbb{E}\left(f_m(X,\theta)f_\ell(X,\theta)\right) = \frac{1}{N}\mathbb{E}\left(f_m(X,\theta)f_\ell(X,\theta)\right).$$

The above means that the efficient weighting matrix in the second step — the inverse of the variance-covariance matrix of the moments — can be found as

$$W = \left(N \cdot \widehat{\Omega}\right)^{-1}$$

Let $D = \frac{\partial}{\partial\theta'}\mathbb{E}(f(X_n,\theta))$. The asymptotic variance of the GMM estimator is

$$\Sigma = (D'WD)^{-1}D'WSWD(D'WD)^{-1}.$$

To avoid numeric differentiation of the vector of moments, we compute the standard errors of the estimates using bootstrap.

E Details of the Results

E.1 Women's estimates

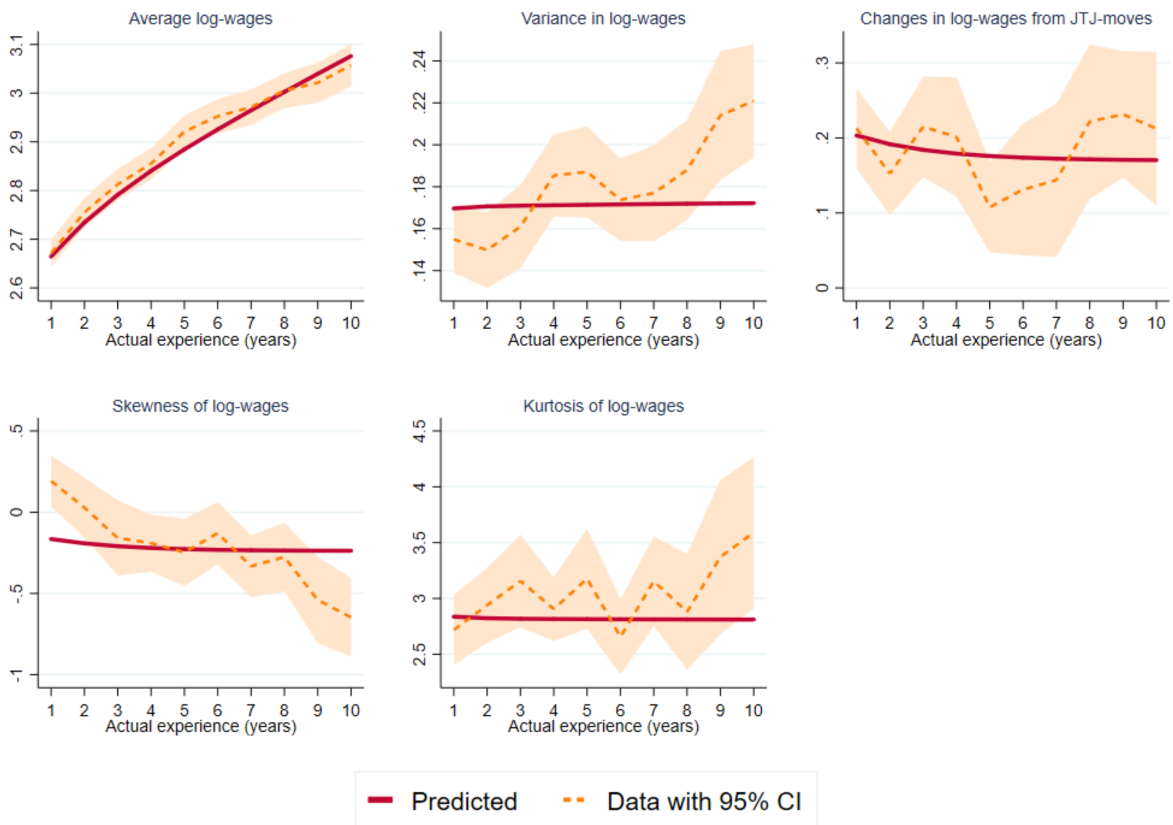


Figure 8: *Fit of the targeted moments for college-educated women*

E.2 Men's estimates

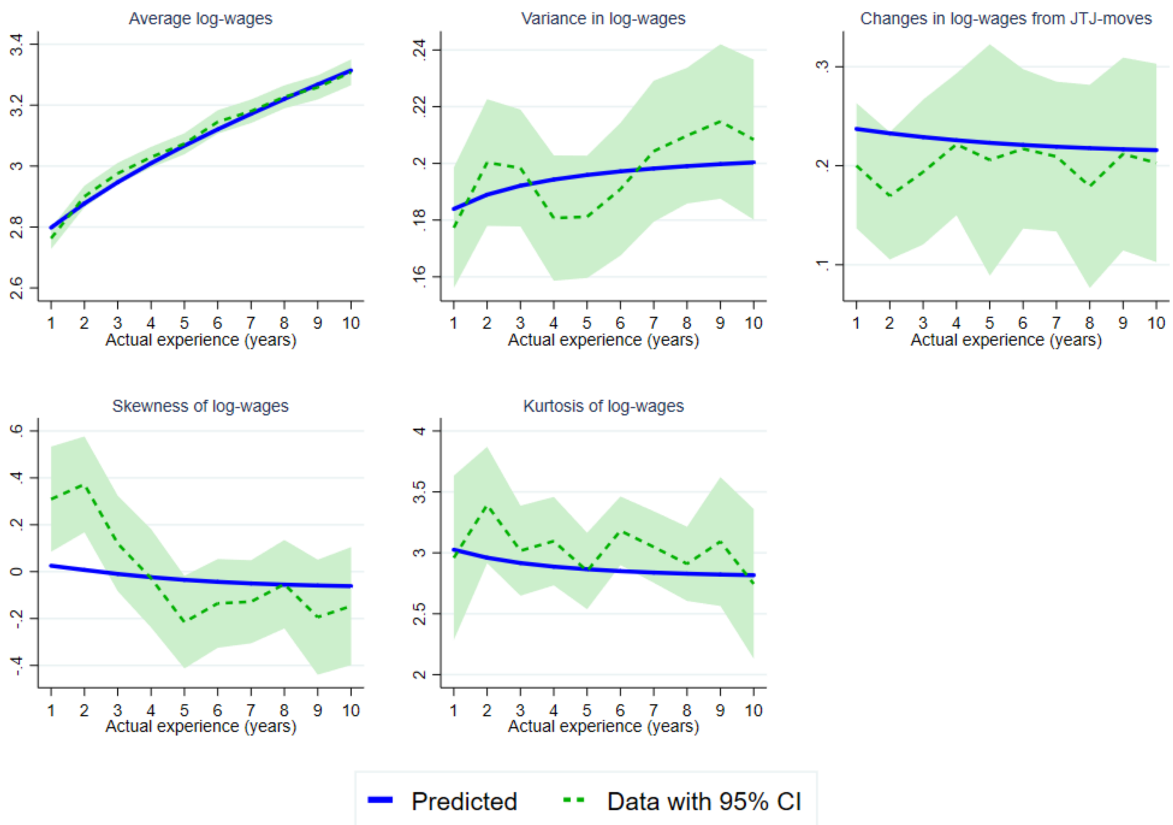


Figure 9: *Fit of the targeted moments for college-educated men*

E.3 Counterfactual policy exercises

E.3.1 Increased arrival rate of offers for employed women

The job-finding rate of employed women, λ_e, is in fact higher than that of men's. In Figure 10 we decrease λ_e by 7.9% to equalize if to men's level. In terms of human capital levels, such a change has no effect, since it does not affect the amount of actual experience that women accumulate, as reflected in Figure 10a. At the same time, the effect on the human capital prices would be substantial (see Figure 10b). For the firms, decreased efficiency of employed search means less competition for employed workers: it is harder to poach workers, and at the same time, firms' employees are less likely to be poached. This decrease in competition pushes the offers down. For the workers, the value of employment decreases, bringing the reservation rate up, which exerts an upward pressure on the lower rungs of the ladder, dampening the decrease of the lowest equilibrium offers. These effects are reflected in Figure 10b: the prices profile decreases more for more experienced women—those who are more likely to reach the higher rungs of the ladder—and becomes steeper relative to the benchmark.

Table 4: Parameter Estimates for College Educated men

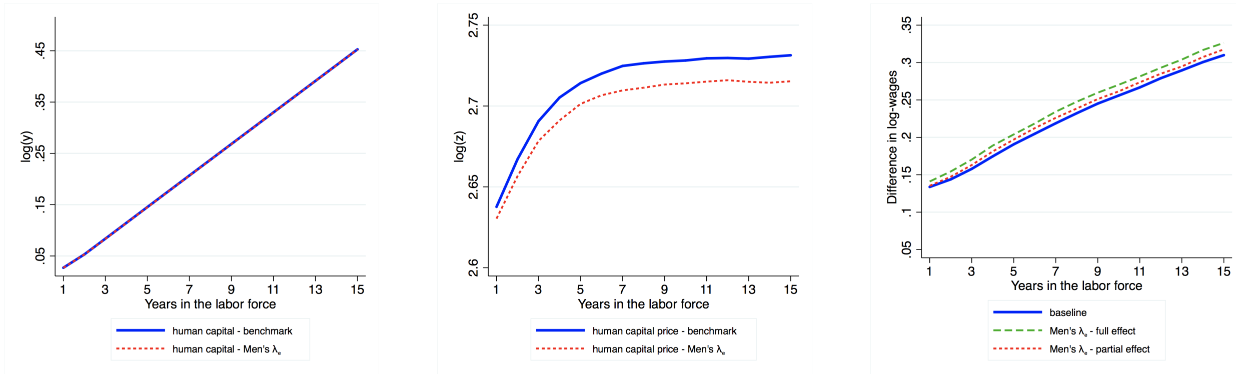
Estimates from data		Jointly estimated parameters	
δ	0.0128	$\underline{p}$	15.2111 (0.1106)
γ_1	0.0071	$\overline{p}$	68.8595 (6.1322)
γ_2	0.5319	κ_1	0.2869 (0.0112)
γ_3	0.0842	κ_2	35.4669 (1.5964)
λ_e	0.0322	ρ	0.0036 (0.0000)
λ_u	0.2373	$\underline{\varepsilon}$	0.2722 (0.0016)
η	0.9555	$\overline{\varepsilon}$	51.0753 (0.0152)
r	0.0041	α_1	2.4794 (0.1384)
ϕ	0.0021	α_2	0.8836 (0.2675)
		b	0.0727 (0.2167)

Note: This table reports the point estimates for college-educated men.

In terms of the impact on the gender wage gap, the partial effect of the policy is rather small and only reflects a slower rise up the fixed ladder of offers. The total effect, however, which incorporates endogenous changes in the ladder itself, is almost three times stronger and is most pronounced for more experienced women for the reasons just described above: the gap increases by 0.007 log-points (or 7.2%) at the onset of workers' careers and by 0.015 log-points (which corresponds to 5.2% as the gap increases) in years 11-15.

E.4 Quantifying the components of the gap

Figure 10: *Higher offers arrival rate in employment*



(a) *Average human capital* ***(b)*** *Average human capital price* ***(c)*** *The gender wage gap*

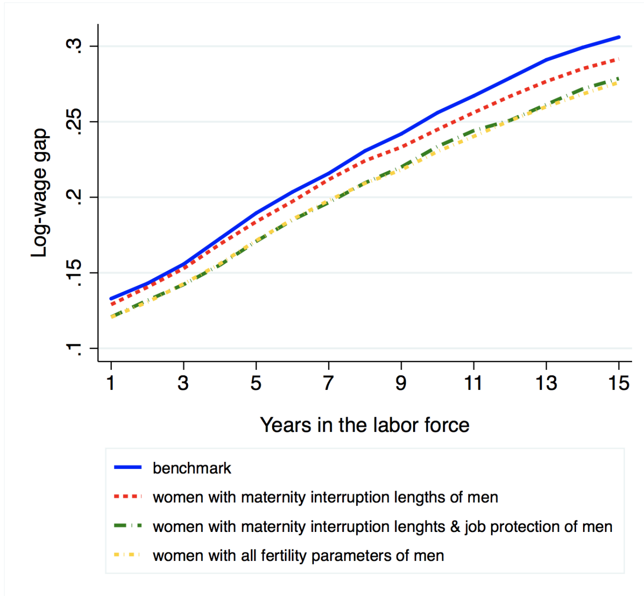
Note: *The figure shows the effect of a 7.9% decrease in the offers arrival rate, λ_e, to equalize it to men's level. Panel (a) shows the effect on human capital profile, Panel (b) shows the effect on the average wage rate profile; in Panel(c), the baseline gap in log-wages between men and women is depicted with a solid blue line, the dotted red line shows the partial effect of a change in the parameter whereas the dashed green line shows the total effect that includes equilibrium responses of the firms.*

In Figure 11, we show the effect of the fertility-related parameters of men. We start by decreasing the average length of the job-protected maternity leave of women by equalizing γ_2 and γ_3 between men and women. This reduces the gap by 0.003 log-points (or 2.3%) in the first 5 years of potential experience and by 0.013 log-points (or 4.6%) in years 11-15. Then we also equalize the proportion of women who get an opportunity to go back to their previous job to the rate of men. The combination of these two changes reduces the gap by 0.014 log-points (9.13%) in years 1-5 and by 0.027 log-points (9.40%) in years 11-15. Equalizing the fertility rate between men and women has virtually no additional impact on the gap since the number of children that men and women have are very similar in the data. Altogether, the differences in fertility-related parameters account for roughly 0.021 log-points 9.5% of the gender wage differential in the first 15 years of a career, and that these parameters account for 0.018 log-points (10.21%) of the gap *opening* over the first 15 years of potential experience.[30]

In Figure 12, we analyze the effect of gender differences in the labor mobility parameters—job finding and separation rates. We start with increasing women's offers arrival rate in unemployment λ_u to the men's level (a 16.4% increase). This leads to a 0.03 log-points (19.52%) reduction of the gap in the first 5 years of a career, and to a 0.032 log-point

[30] The benchmark gap opens by 0.173 log points over the first 15 years in the market, and with fertility parameters equalized it opens by 0.155 log points.

Figure 11: *Implied wage gap giving women the fertility parameters of men*



Note: *The figure shows how the gap in log-wages by potential experience changes when we successively give women the fertility-related parameters of men.*

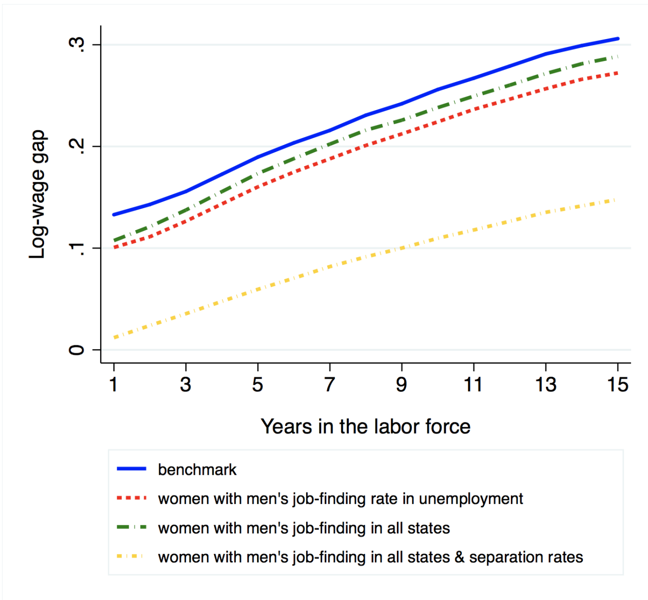
(11.40%) reduction in years 11-15. Next, we equalize the arrival rates of women's offers in employment to the level of men (a decrease of 7.9% in λ_e). Since in this case women's parameter was "better" than men's, this change offsets a bit the gains from the increase in the job-finding rate λ_u so that the gap is now reduced by 0.02 log-points (12.91%) in years 1-5 and by 0.018 log-points (6.33%) in years 11-15, relative to the benchmark. At the last step, we equalize the separation rate of women to the level of men. This represents a striking 36.8% decrease in the separation rate and has a massive impact on the life-cycle gap dynamics. In particular, eliminating the differences in the transition rates would reduce the gap by 0.139 log-points (64.30%) on average in the years 1-15 of potential experience. Furthermore, these transition rates differences account for approximately 0.037 log-points (21.51%) of the gap expansion over the same years.

Table 5: *Closing the gap between men and women by equalizing their parameters*

Equalizing	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV	XV	XVI
–	baseline															
fertility		✔				✔	✔	✔			✔	✔		✔		✔
transitions			✔			✔			✔	✔	✔	✔			✔	✔
$\Gamma(p)$				✔			✔		✔		✔		✔	✔	✔	✔
ρ					✔			✔		✔		✔	✔	✔	✔	✔
gap 1-5	0.1598	0.1428	0.0371	0.1001	0.1786	0.0193	0.0825	0.1614	-0.0282	0.0418	-0.0472	0.0243	0.1196	0.1004	-0.0224	-0.0430
gap 11-15	0.2874	0.2584	0.1343	0.2261	0.2431	0.1026	0.1970	0.2109	0.0648	0.0715	0.0315	0.0363	0.1815	0.1473	0.0016	-0.0354
average gap	0.2257	0.2030	0.0875	0.1659	0.2126	0.0628	0.1419	0.1878	0.0205	0.0578	-0.0057	0.0317	0.1519	0.1257	-0.0085	-0.0381
gap opening	0.1762	0.1600	0.1408	0.1758	0.0865	0.1206	0.1578	0.0637	0.1366	0.0453	0.1178	0.0214	0.0847	0.0630	0.0380	0.0167

Note: The table reports the gap in log-wages between men and women when different sets of parameters are equalized. Column I shows the gap predicted by the model at baseline values; column II equalizes the fertility parameters of women to the level of men; column III equalizes the labor mobility parameters to the level of men; column IV equalizes the distribution of firms' productivities and column IV equalizes the human capital accumulation rate. Then, in columns VI–XVI we additively equalize these sets of parameters, one by one. Column VI shows the predicted gap when...

Figure 12: *Implied wage gap giving women the transition rates of men*



Note: *The figure shows how the gap in log-wages by potential experience changes when we successively give women men's transition-rate parameters outside of fertility episodes.*