Labor Market Beliefs and the Gender Wage Gap

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Abstract

We study how labor market beliefs shape the gender pay gap within an equilibrium search model that incorporates subjective expectations about wage offers, arrival rates, and separation rates. Using the Survey of Consumer Expectations to estimate the model, we find that biased beliefs account for 23% of the gender wage gap. While correcting beliefs reduces the wage gap, the effect is small compared to equalizing women's true labor market parameters to those of men. Moreover, only the latter reduces gender disparities in both wages and welfare.

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1 Introduction

When individuals decide whether to accept a job offer, their expectations about various labor market outcomes—such as the likelihood of finding a new job—play a central role. However, these expectations are often biased, with individuals being, on average, overly optimistic about job-finding prospects and wage offers (see Mueller and Spinnewijn (2023) for a review of empirical findings). This paper takes a first step in exploring the role of labor market expectations—documented to differ between men and women (Cortés et al., 2023; Kiessling et al., 2024)—in shaping the gender wage gap. To do so, we use an equilibrium search model in which expectations transmit to realized wages through their impact on reservation wages.

Understanding the contribution of expectations to the gender wage gap is important for informing policy debates, as it opens doors for information-based interventions, such as pay transparency policies, that help workers adjust their expectations. We make two contributions. First, a decomposition of wage differentials shows that biased beliefs explain approximately 23% of the gender wage gap, with the remainder driven by differences in true labor market parameters and observables. Importantly, biased beliefs contribute more to the wage gap among non-parents, while the gap among parents is primarily driven by true labor market parameters. This suggests that assuming rational expectations when studying the mechanisms behind the gender wage gap could lead to misleading conclusions, particularly in early-career years. Second, we show that correcting biased beliefs reduces the wage gap, but the impact is far smaller than equalizing women's true labor market parameters—such as wage offer distributions, arrival rates, and separation rates—with those of men. Finally, we also show that a gender-neutral labor market not only reduces the wage gap but it also reduces welfare inequality.

To study the relationship between labor market beliefs, wages, and welfare, we incorporate subjective expectations into a standard labor market model with on-the-job search. Specifically, we allow workers to have biased beliefs about realizations of future wage offers, the arrival of offers, and separations into unemployment. In equilibrium, labor market beliefs determine realized wages and welfare by shaping workers' reservation wages. For instance, when workers overestimate the likelihood of receiving a job offer while unemployed, they perceive their outside option – the value of remaining unemployed – to be higher than it actually is. As a result, they set a higher reservation wage and become more selective about the jobs they are willing to accept. While this selectivity results in higher realized wages when employed, it also prolongs their unemployment duration, ultimately reducing their welfare.

We estimate model parameters by maximum likelihood using data from the Survey of Consumer Expectations and its supplement, the Labor Market Survey. To incorporate individual heterogeneity, model parameters vary with individual characteristics and differ for men and women, as in Flinn et al. (2020). We focus on working-age individuals between 2015 and 2019. The panel survey provides standard information on employment and wages, as well as a set of questions designed to capture expectations about future job opportunities and wage offers. We begin by empirically examining the model mechanisms and predictions using the survey measures of expectations and reservation wages. We show that both men and women tend to be optimistic about the number of job offers and wages they anticipate receiving over a four-month period. However, men exhibit greater optimism than women, particularly regarding salary expectations. This aligns with recent studies of college graduates by Kiessling et al. (2024) and Cortés et al. (2023). Consistent with the model, expectations about offers are positively associated with reservation wages. In particular, expectations explain a large proportion of observed gender differences in reservation wages (about 60% of the residual gap). We confirm that this result is not driven by differences in other observable factors, including risk aversion.

The model successfully replicates key features of the data, closely matching observed gender differences in expectations. Specifically, the model-implied women-to-men wage ratio accounts for approximately 94% of the ratio observed in the data. Using estimated model parameters, we first decompose the gender wage gap into three components: differences in observable characteristics, biased beliefs, and true labor market parameters. Our results show that gender differences in biased beliefs contribute 23% to the gender wage gap, while differences in the true labor market parameters explain 42% of the gap. We extend the baseline analysis in two ways. First, we depart from risk neutrality and allow for gender differences in risk aversion. Calibrating risk aversion for men and women following Cortés et al. (2023), we find that although the role of biased expectations diminishes, it remains substantial, accounting for approximately 15% of the gender pay gap. Second, we separately analyze the relative contribution of biased beliefs and true labor market parameters to the gender wage gap for parents and non-parents. Among non-parents, the contribution of biased expectations is larger, accounting for approximately 34% of the wage gap, while differences in labor market parameters contribute 21%. In contrast, for parents, the wage gap is primarily driven by differences in true labor market parameters, with biased expectations playing a small role.

Next, we conduct two policy-relevant counterfactuals. First, we correct beliefs about labor market parameters for both men and women. Doing so reduces the residual wage gap by about 2 percentage points but increases the welfare gap. Since both men and women are optimistic, aligning beliefs with objective labor market conditions reduces their perceived value of unemployment. This leads to lower reservation wages and, consequently, lower average wages. The effect is more pronounced for men, as they are more optimistic, resulting in a reduction of the observed gender wage gap. On the other hand, lower reservation wages make workers less selective, leading them to exit unemployment faster, which increases the welfare of both men and women to its maximum value. Again, since men are more optimistic, aligning their beliefs increases their welfare more than women's, resulting in an increase in the welfare gap. Interestingly, when we correct only beliefs about the wage distribution—mimicking an information shock akin to pay transparency policies—the gender wage gap decreases modestly by about half a percentage point (2.8%). This reduction is primarily driven by a decline in men's pay, as their beliefs about the offer distribution deviate further from the true wage offer distribution compared to women's. These findings align with recent empirical evidence on the effects of pay transparency policies (Duchini et al., 2022; Bennedsen et al., 2022; Gulyas et al., 2021).

In the second counterfactual, we equalize true labor market parameters, by giving women the same parameters as men, while keeping belief biases unchanged. This reduces the gender wage gap by 60%, with the wage offer distribution being the main driver. Interestingly, increasing only women's offer arrival rates to match those of men leads to an increase in the gender wage gap. This is due to the larger rise in women's offer arrival rate while employed, which lowers the value of unemployment, thereby reducing their reservation wages and observed average wages. As in the decomposition exercise, we observe differences between parents and non-parents in the two counterfactual scenarios. Correcting beliefs leads to only a small change in wage differences for both groups. However, equalizing true labor market parameters—specifically the wage offer distribution—completely eliminates the gender wage gap for parents, but not for non-parents. While our model does not pinpoint the specific drivers of differences in the wage offer distribution, this finding supports the theory of compensating differentials (Rosen, 1986). Women, particularly after having children, may place a higher value on non-wage amenities, such as flexible work arrangements (Goldin, 2014), which could lead them to lower-wage jobs, consistent with findings by Morchio and Moser (2024).

Our results provide valuable insights into the ongoing debate about the causes of the gender wage disparity and the policy tools that can address it. Overall, they suggest that reducing gender disparities in the wage offer distribution is more effective in reducing both pay and welfare inequality than policies focused solely on providing wage information. For example, correcting biased beliefs actually widens the gender welfare gap, as men experience larger welfare gains from having unbiased beliefs than women do. Efforts to equalize hiring opportunities may also have unintended consequences: as women adjust their expectations to having more job opportunities while employed, they may accept lower-paying jobs while unemployed, ultimately exacerbating the wage gap.

Related literature Our findings contribute to the literature analyzing gender differences in job search behavior and outcomes. Specifically, our work builds on to the literature that studies the gender wage gap through the lens of equilibrium search models (e.g. Bowlus, 1997; Flabbi, 2010; Liu, 2016; Amano-Patiño et al., 2020; Flinn et al., 2020; Xiao, 2021; Morchio and Moser, 2024).

A common assumption in this literature is that individuals have rational expectations, implying that they know their labor market prospects. To the best of our knowledge, this paper is the first to incorporate subjective beliefs into a job search framework to study gender differences in labor market outcomes. By doing so, we shed light on the transmission of expectations to wages and their implications for the gender pay gap. In addition, while most prior studies estimate different search parameters by gender and education groups, we allow job search model parameters and their expectation counterpart to vary by gender and a broad set of worker characteristics, as in Flinn et al. (2020), including parenthood status. This allows us to explore heterogeneity in the contribution of biased beliefs relative to true labor market parameters along the parenthood dimension. Our results show that for non-parents, both gender differences in biased expectations and true labor market parameters are important in explaining the pay gap. However, for parents, the pay gap is primarily driven by differences in actual labor market parameters. This suggests that assuming rational expectations when studying the life-cycle gender pay gap can lead to qualitatively different conclusions about the mechanisms behind the pay gap and the effects of policy, particularly in early career years.

A few empirical studies have highlighted gender differences in salary expectations among college graduates (Reuben et al., 2017; Cortés et al., 2023; Kiessling et al., 2024). For example, Cortés et al. (2023) find that female students exhibit lower levels of overoptimism, which may explain why they accept job offers significantly earlier than their male counterparts. Kiessling et al. (2024) document a large gender gap in wage expectations, which mirrors actual wage disparities, and provide evidence linking this gap to differences in expected asking wages and reservation wages. By embedding subjective expectations into a canonical search model of the labor market, our findings not only provide support for existing evidence but also quantify the role of biased expectations in driving the gender pay gap. In doing so, we find that while biased beliefs contribute to the gender pay gap, addressing these biases alone does not close the wage gap and, at the same time, widens the welfare gap.

Our paper also speaks to a growing literature that studies the implications of biased expectations for labor market outcomes. Mueller et al. (2021) show that optimistic bias in workers' job-finding beliefs leads to less job search. Similarly, Conlon et al. (2018) find that expectations about future wage offers are a key feature to understanding observed patterns of reservation wages. Closely related to our work, Balleer et al. (2024) link biases in job-finding and separation risk expectations to wage disparities between East and West Germany. Our paper complements this literature in two ways. First, we examine the role of biases in expectations—not only about wages but also about job offer arrival rates and separation rates—in shaping wages through their impact on reservation wages. Second, we shed new light on how gender differences in biased beliefs contribute to observed gender pay gaps.

Layout The remainder of the paper proceeds as follows. The next section presents the model. Section 3 describes the estimation procedure, Section 4 summarizes the estimation results and decomposes the gender wage gap into components due to observables, biased beliefs, and true labor market parameters, and Section 5 details our policy counterfactual exercises and results. Section 6 concludes.

2 Model

In this section we introduce a search model of the labor market in which we allow workers to have expectations about labor market parameters, such as arrival rates, wage offers, and separation rates, that deviate from the true parameters. Our modeling framework is based on the canonical job-ladder model outlined by Burdett (1978).

Workers There is a continuum of risk-neutral workers that share the same discount rate r. They differ in their gender $g \in \{f, m\}$ and type x_i. In our application, x_i is assumed to be a linear combination of observed individual characteristics with the weights attached to each characteristic allowed to differ across model parameters and genders.

Job Search Each gender-x_i group represents a separate labor market, such that model parameters are specific to both gender and x_i. To simplify notation, the gender subscript g is omitted in the following discussion. The model structure is identical for men and women. Workers search for jobs both while employed and unemployed, randomly encountering offers posted by firms. When unemployed, workers receive a flow value of unemployment, $b(x_i)$, and meet firms at the rate $\lambda_u(x_i)$. When employed, workers earn a wage w, continue searching on the job, and receive job offers at the rate $\lambda_e(x_i)$. Both job arrival rates are assumed to be exogenous. Wage offers are drawn from the distribution $G(w|x_i)$, which is independent of the worker's employment state. Additionally, worker-firm matches are dissolved at an exogenous rate $\delta(x_i)$.

Beliefs The literature typically assumes that workers have rational expectations about matching probabilities, separation rates, and wage offers. In contrast, we allow workers' expectations to deviate from the true labor market parameters. We do not explicitly model how these beliefs are formed. For a worker of type x_i, the believed arrival rates of job offers are $\lambda_u^B(x_i)$ when unemployed and $\lambda_e^B(x_i)$ when employed. Employed workers also form beliefs about the job separation rate, $\delta^B(x_i)$, and all workers believe wages are drawn from a distribution with the cdf $G^B(w|x_i)$. An optimistic bias arises when, for example, $\lambda_u^B(x_i) > \lambda_u$, meaning the worker overestimates the probability of finding a job while unemployed. Conversely, a pessimistic bias occurs when, for example, $\delta^B(x_i) > \delta(x_i)$, implying the worker overestimates the likelihood of job separation.

2.1 Reservation Wage

For an unemployed worker of type x_i, the reservation wage $R(x_i)$ is the wage offer at which they are indifferent between accepting or rejecting an offer, based on their beliefs. Thus, it satisfies $E^B(R(x_i), x_i) = U^B(x_i)$, where $E^B(R(x_i), x_i)$ is the perceived value of being employed with the reservation wage $R(x_i)$ and $U^B(x_i)$ is the perceived value of unemployment for a worker of type x_i. The latter is defined as:

$$rU^B(x_i) = b(x_i) + \lambda_u^B(x_i) \int_{R(x_i)}^{\bar{w}} E^B(w, x_i) - U^B(x_i)\, dG^B(w|x_i) \tag{1}$$

where $b(x_i)$ is the flow value of unemployment, and $\lambda_u^B(x_i)$ and $G^B(w|x_i)$ are, respectively, the worker's beliefs about the job arrival rate and the wage offer distribution. Analogously, the believed value of an employed worker of type x_i in a job with wage w is given by

$$rE^B(w, x_i) = w + \lambda_e^B(x_i) \int_{w}^{\bar{w}} E^B(w', x_i) - E^B(w, x_i)\, dG^B(w|x_i) + \delta^B(x_i)[U^B(x_i) - E^B(w, x_i)]. \tag{2}$$

where λ_e^B, $\delta^B(x_i)$ and $G^B(w|x_i)$ are, respectively, the worker's beliefs about the job arrival rate on-the-job, likelihood of separation, and the wage offer distribution. Using these definitions, the reservation wage $R(x_i)$ for an unemployed worker of type x_i is

$$R(x_i) = b(x_i) + \left[\lambda_u^B(x_i) - \lambda_e^B(x_i)\right] \int_{R(x_i)}^{\bar{w}} \frac{1 - G^B(w|x_i)}{r + \delta^B(x_i) + \lambda_e^B(x_i)[1 - G^B(w|x_i)]}\, dw, \tag{3}$$

that is, the sum of the flow value of unemployment plus the *perceived* foregone option value of receiving job offers while unemployed. If workers are optimistic about the arrival rate of offers while unemployed $\left(\lambda_u^B(x_i) > \lambda_u(x_i)\right)$, the perceived value of search increases, raising the reservation wage. Conversely, if workers are optimistic about offers arrival on-the-job $\left(\lambda_e^B(x_i) > \lambda_e(x_i)\right)$, the perceived value of search decreases, lowering the reservation wage. When workers believe they face a more favorable distribution of job offers, their reservation wage may increase or decrease: if they are more (less) optimistic about receiving job offers while unemployed compared to when employed, their reservation wage increases (decreases), as the perceived option value of search rises (falls). Finally, employed workers in a job with wage w accept any job that offers a higher wage.

2.2 Steady State

In steady state, the flow creation and flow destruction of matches for each type of worker must exactly balance. Therefore, the unemployment rate for worker type x_i is

$$u(x_i) = \frac{\delta(x_i)}{\delta(x_i) + \lambda_u(x_i)[1 - G(R(x_i)|x_i)]}. \tag{4}$$

Moreover, the measure of workers of type x_i below a certain wage w must also remain constant in the steady state equilibrium. Let $F(w|x_i)$ denote the cumulative distribution of observed wages. This is determined in steady state by the following flow-balance equation,

$$\lambda_u(x_i)[G(w|x_i) - G(R(x_i)|x_i)]u(x_i) = [\delta(x_i) + \lambda_e(x_i)[1 - G(w|x_i)]]F(w, t|x_i)(1 - u(x_i)), \quad (5)$$

where the left-hand side is the inflow into the stock of type-x_i workers employed below wage w, and the right-hand side is the outflow from the stock of type-x_i workers employed below wage w. From Equation 5, the mean of the observed wage distribution can be derived as follows[1]:

$$\mathbb{E}[w|x_i] = \frac{\delta(x_i)}{1 - G(R(x_i)|x_i)} \int_{R(x_i)}^{\infty} wg(w|x_i) \left[\frac{\delta(x_i) + \lambda_e(x_i)[1 - G(R(x_i)|x_i)]}{\{\delta(x_i) + \lambda_e(x_i)[1 - G(w|x_i)]\}^2} \right] dw. \quad (6)$$

Differences in average wages across worker types are driven by differences in the speed at which workers climb the job ladder, determined by the arrival rate on-the-job $\lambda_e(x_i)$) and the separation rate $\delta(x_i)$, the true wage offer distribution ($G(w|x_i)$), and differences in individuals' willingness to accept a job captured by the reservation wage ($R(x_i)$).[2] Combining Equation 6 with Equation 3, one can conclude that workers' beliefs about labor market parameters influence the observed average wage solely through the reservation wage. Labor market beliefs influence the perceived value of job search, thereby affecting the minimum wage workers are willing to accept for employment.

2.3 Discussion of Model Assumptions

We now discuss some of our modeling assumptions and their implications. First, we assume workers are risk-neutral. This assumption allows us to reconcile our single-agent search model with a joint-search framework. Men and women often live in the same household, so their labor supply decisions are likely jointly determined. Under risk neutrality, household decision-making is independent as the household's maximization problem can be separated into two individual maximization problems (Guler et al., 2012). As a robustness, we also estimate a version of our model incorporating gender differences in risk-aversion as in Cortés et al. (2023) and discuss its quantitative implications (Appendix D.1).

Second, we assume no interdependence between labor market beliefs and their true counterpart. This assumption is grounded on empirical evidence in Table A.5 showing that workers' expectations are not significantly correlated to their job search effort in terms of applications sent, which suggests a rather weak link between workers' expectations and future realizations through search behavior. In line with this evidence, Adams-Prassl et al. (2023) show that workers perceive a low return to

[1] For more details on the derivation, see Appendix B.

[2] The upper limit of the support of the observed wage distribution is a result of the functional form assumption used in the estimation, which is explained in detail below.

additional hours of search, lending support to the common practice of assuming constant finding rates (e.g. Mueller et al., 2021). Taken together, this suggests that expectations affect average wage through the reservation wage rather than through true parameters. In the counterfactual analysis (Section 5), we explore the role of gender differences in the *bias* of labor market beliefs, defined as the log difference between beliefs and actual values, and not their *level*, canceling out any differences in true parameters due to differences in expectations.

Third, we assume firms make "take-it-or-leave-it" offers, leaving no scope for wage bargaining. This assumption aligns well with the data used to estimate the model, where approximately 70% of respondents report receiving "take-it-or-leave-it" offers rather than engaging in negotiations over pay. Importantly, when estimating the model we allow the exogenous distribution of offers $G(w|x_i)$ to vary by gender. This approach implicitly captures gender-specific employer pay components that may arise from differences in bargaining (Card et al., 2016; Biasi and Sarsons, 2021; Roussille, 2022), but also taste-based discrimination (Becker, 1971; Flabbi, 2010), or gender-specific preferences for job attributes (Rosen, 1986; Goldin, 2014; Morchio and Moser, 2024). Note that to the extent that differences in the wage offer distribution $G(w|x_i)$ by gender might arise due to gender differences in expectations, the counterfactual exercises in Section 4 and Section 5 arguably yield a lower bound of the impacts of biased beliefs on the gender gap.

Finally, we abstract from belief updating and respective priors. Although this is no doubt an important aspect to understand *why* men and women may have different beliefs, we leave it to future work to study the case where workers learn over time about the actual transition probabilities and offer distributions. We argue that this is not a key aspect of understanding *how* differences in beliefs matter for the wage gap. Overall, we view the results in this paper as shedding light on which beliefs matter most, thus guiding future research toward understanding the formation of the beliefs that have the largest influence on the gender wage gap.

3 Estimation Strategy

We estimate model parameters by maximum likelihood, using the Survey of Consumer Expectations (SCE) and its supplement, the Labor Market Survey (LMS). In this section, we first describe the dataset and provide descriptive evidence on gender differences in labor market beliefs and how these beliefs relate to reservation wages. Next, we explain how the model parameters vary by worker type and outline the construction of the likelihood function.

3.1 Data and Descriptive Evidence

The SCE surveys a representative sample of around 1,300 US household heads on a monthly basis, with each individual participating for up to 12 months. Active panel members—those who completed the SCE in the previous three months—are eligible for the LMS, allowing up to three inclusions in the supplement during their tenure. The LMS reports information on job search behavior, beliefs about job offers, salary expectations, reservation wages, and labor market outcomes such as employment duration, non-employment spells, and wages. Demographic information is available through the SCE.

3.1.1 Sample and Main Variables

Sample Selection We use an unbalanced panel from the SCE, covering the period from November 2015 to November 2019 and restricted to individuals aged 20 and 65 years old with non-missing data.[3] We also drop individuals whose wages (for current job, offers, or expectations) are less than $4/h. This provides a final dataset with 8056 observations from 4238 unique individuals. Panel A, Column 1 in Table 1 describes the main characteristics of our sample. Individuals are, on average, 45.4 years old, around 81% are white, and almost 43% have a college degree. Men make up slightly more than half of the sample. The sample aligns well with the demographic characteristics of household heads in the Current Population Survey (CPS) over the period from 2015 to 2019 (Table A.1).

Men and women differ in several dimensions, as shown in Columns 2 and 3 of Table 1 (Column 4 reports the p-value of the equality test of the means across gender). On average, women are 1.9 years older and 86.5% of them are white. The largest gender difference is observed in terms of education. Mirroring the overall US population, women are more educated: 47.6% of them have a college degree or more, which compares to 37% of men. One potential worry is that women who are household heads are different than the average woman in the US and more similar to the average men, specifically in the labor market. Using CPS data, Table A.2 and Table A.3 show that this is not the case. Although women who are household heads are slightly different than other women in terms of demographic characteristics (Panel A of Table A.2), these two groups look very similar to each other in the labor market; not only in terms of the employment rate or hours worked (Panel B of Table A.2), but also in terms of the occupations in which they work (Table A.3).

Labor Market Status We classify respondents as employed if they worked for pay at the time of the survey and as non-employed if they were not working and did not report being permanently disabled or unable to work. This broader definition of job seekers differs from the CPS definition, which includes only those who are not employed, available to work, actively sought work in the past four weeks, or were on temporary layoff. We adopt this wider scope based on findings by Braun (2024), which show that hires from individuals classified as out of the labor force have risen

[3] We drop individuals with missing information on the education level, race, marital status, children, reservation wage, and the perceived probability of receiving a job offer.

significantly in recent decades. Consistent with this, around 2/3 of those in our sample who would be considered out of the labor force under CPS criteria report a positive likelihood of receiving a job offer or being employed in the next four months. This suggests that limiting job seekers to those who looked for a job in the past 4 weeks might not accurately identify potential workers.

Hourly Rates The LMS reports pay-related information in annual terms but does not include data or hours worked or desired hours. Since women generally work fewer hours than men (Goldin, 2014), converting annual earnings into hourly rates is important for our analysis. To estimate annual hours worked, we use the average weekly hours reported in the CPS monthly data and assume individuals work 50 weeks per year.[4] For employed respondents, we impute hours worked based on the average weekly hours worked by part-time and full-time workers in the CPS data, disaggregated by gender, education, and industry. Using this approach, employed women in our sample work an average of 38 hours per week compared to 42 hours for men. In a comparable CPS sample, women work an average of 37 hours per week and men 42 hours per week, supporting our imputation method.[5] We further assume that reservation wages and expected earnings reported by part-time workers correspond to part-time work, while those reported by full-time workers reflect full-time work. For unemployed respondents, we assume their reservation wage and earnings expectations refer to full-time work, and we estimate their weekly hours based on the averages for full-time workers, broken down by gender and education level. Although the LMS does not specify whether the respondents are looking for full-time or part-time work, CPS data shows that 87% of the unemployed are looking for full-time jobs. Thus, this assumption seems reasonable.

Job offers: Beliefs and Realizations The LMS asks all respondents, regardless of their current employment status: "*What do you think is the percent chance that within the coming four months, you will receive at least one job offer?*".[6] If respondents report a non-zero probability, they are subsequently asked more detailed questions about their expectations regarding job offers and potential salaries. Specifically, the survey asks:

- "*Over the next 4 months, how many job offers do you expect to receive? Remember that a job offer is not necessarily a job you will accept.*"

[4] We use CPS monthly data spanning the period from 2015 and 2019 and restrict the sample to household heads between 20 and 65 years old. We define part-time workers as those individuals working less than 35 hours and full-time workers as those working more than 35 hours. We consider four education levels: less than high school, some college, a bachelor's degree, and more than a bachelor's degree. To compute the average hours worked we use the CPS variable $uhrswork1$, which measures the usual number of hours per week the respondent reports being at their main job.

[5] Alternatively, one could apply the method used by Conlon et al. (2018), which assumes that full-time workers put in 40 hours per week for 52 weeks per year, and part-time workers 20 hours per week for the same period. However, this approach does not capture gender differences in hours worked. Reassuringly, our results are robust to the use of Conlon et al. (2018)'s methodology.

[6] For those respondents currently employed, the question wording is slightly different and asks about job offers from *another employer.*

- "*Think about the job offers that you may receive within the coming four months. Roughly speaking... (i) what do you think the average annual salary for these offers will be?*" *and (ii) ...what do you think the best annual salary for these offers will be?*".

We use responses to the first two questions to gauge beliefs about job offer arrival rates, while the third question helps us infer expectations regarding the distribution of wage offers. A unique feature of LMS is that it also collects data on job offers received, regardless of whether the job offer was accepted. Respondents are asked:

- "*How many job offers did you receive in the last 4 months? Remember a job offer is not necessarily a job that you accepted.*"
- "*Thinking about the 3 best job offers that you received in the last 4 months, What was their annual salary?*"

These responses allow us to calibrate the true job offer arrival rates and the true wage offer distribution in the model. Panel B and C in Table 1 present summary statistics on labor market expectations and realizations, highlighting substantial gender differences in the raw data. On average, respondents expect 0.8 job offers, reflecting that a majority of workers do not expect any job offer at all (the median is 0). Women expect to receive more offers (0.86) than men (0.77), but expect to be offered a lower salary. The average expected salary for women is around 70% of that for men, a gap which also extends to the best wage offers. Realized salary offers are lower than expectations, with the best-received offer averaging \$27.1 per hour compared to an expected offer of \$32.8. This gap is larger for men (\$7) than for women (\$4).

Separation rate: Beliefs and Realizations To discipline perceived separation rates, we rely on the following survey question asked to employed respondents: " *What do you think is the percent chance that four months from now you will be unemployed?*". The last row of Panel B in Table 1 shows that, on average, about 3% of the employed expect to lose their jobs within the next four months, with no statistically significant difference between men and women. We supplement this data with information on the unemployment probability across the population and employment durations to calibrate parameters associated with the ture separation rate.

Reservation Wage The LMS elicits individuals' willingness to accept future job offers by asking: "*Suppose someone offered you a job today in a line of work that you would consider. What is the lowest wage or salary you would accept (BEFORE taxes and other deductions) for this job?*". On average, men report a reservation wage of \$37.6 per hour, while women report \$26.5, resulting in a women-to-men ratio of about 0.7, which mirrors the raw gender gap in wage expectations (Panel C of Table 1). We use reported reservation wages to infer the flow value of unemployed, as described in Section 3.4.

Table 1: Descriptive Statistics

	Full	Men	Women	p-value
Panel A: Individual Characteristics				
Age	46.0	46.9	45.1	0.000
College degree or more	0.80	0.84	0.76	0.000
Has children ≤ 18	0.40	0.46	0.35	0.000
Married/Has partner	0.65	0.71	0.58	0.000
Panel B: Labor Market Beliefs				
Likelihood receiving offer (%)	24.4	24.3	24.5	0.693
Expected # job offers, next 4 months	0.81	0.77	0.86	0.003
Expected average wage offer, next 4 months	28.3	33.0	22.9	0.000
Expected best wage offer, next 4 months	32.8	38.2	26.6	0.000
Likelihood losing job, next 4 months (%)	3.18	3.30	3.04	0.331
Panel C: Search and Labor Market Outcomes				
Looking for a job (%)	0.20	0.20	0.20	0.000
Reservation wage	32.3	37.6	26.5	0.000
Received # offers, last 4 months	0.33	0.35	0.31	0.092
Offered wage, last 4 months	27.10	31.20	22.20	0.000
Wage	54.70	36.60	25.30	0.000
Unemployment duration (months)	31.0	43.9	63.7	0.000
Employment duration (months)	90.9	100.0	80.0	0.000
# respondents	4483	2 197	2 286	
# observations	8507	4082	4425	

Notes: The table reports means for all respondents in our sample and separately by gender. Pay-related values—expectations and realizations—are reported as hourly amounts in dollars. *Wage*, *Unemployment* and *Employment* duration report the mean for respondents that are employed and non-employed. The sample is a sub-sample from SCE subject to the criteria described in the main text from November 2015 to November 2019.

3.1.2 Descriptive Evidence

Expectations about labor market outcomes—such as job offers and wages—may differ between women and men due to differences in individual characteristics (e.g., education or age) or because they apply to different jobs with varying attributes (Fluchtmann et al., 2024; Lochner and Merkl, 2023). To control for this heterogeneity, we define the gender expectations gap as the coefficient β in the regression,

$$y_{i,t} = \alpha + \beta\, female_i + \gamma' x_{i,t} + \delta_s + \delta_t + \varepsilon_{i,t}, \tag{7}$$

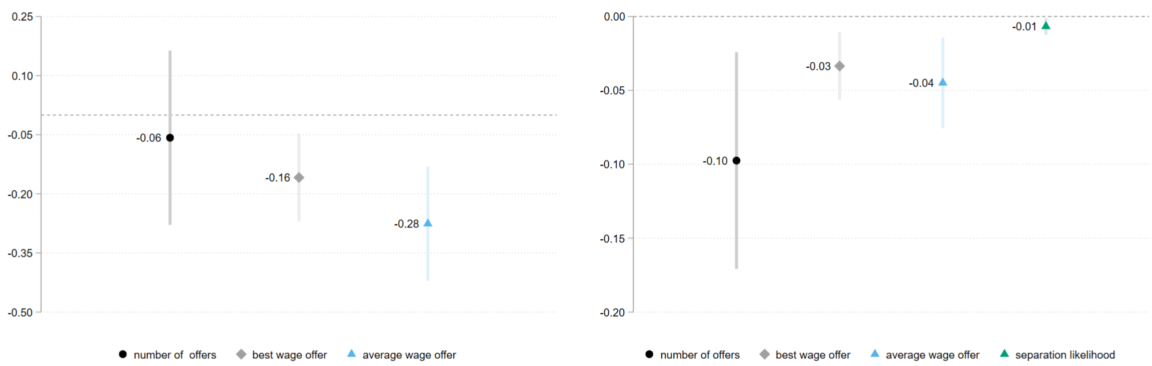
which we estimate separately for employed and non-employed respondents. Here, $female_i$ is a dummy equal to one if the respondent is female, and $x_{i,t}$ is a vector including individual-level characteristics typically used in the gender pay gap literature (e.g., age, education level, race) as well as job search activity (whether an individual search for a job in the last four weeks), employment/non-employment duration and job characteristics. For employed individuals, job characteristics include hourly wages and industry; for non-employed individuals, they include previous hourly wages. This follows Fluchtmann et al. (2024), who find gender differences in applied jobs closely align with observed gender gaps in labor market outcomes.[7] δ_s and δ_t are state and survey date fixed effects, respectively, and $\varepsilon_{i,t}$ is the error term, capturing all unobserved determinants of outcomes for respondent i at time t. We estimate this regression separately for employed and non-employed individuals.

Gender Expectations Gap Figure 1 presents the estimated gender gap in expectations, highlighting significant differences in labor market beliefs between men and women, conditional on the included covariates. First, employed women anticipate receiving fewer job offers over the next four months compared to employed men, with a statistically significant gender gap at the 1% level (Figure 1b). However, among the non-employed, the difference in expectations between men and women is not statistically significant (Figure 1a). Second, regardless of employment status, women consistently expect lower wage offers than men, consistent with findings among college graduates (e.g. Cortés et al., 2023; Kiessling et al., 2024). For the non-employed, the best-expected wage is 16% lower for women, and the average expected wage is 27% lower for women. Among employed women, these gaps are 3% and 4%, respectively, with all differences significant at the 1% level. Third, employed women expect a 1 percentage point lower likelihood of separation compared to men, a difference that is statistically significant at the 5% level.

[7] We confirm the results in the literature using data from the Job Search Supplement of the SCE, which has more detailed information on the application behavior of its respondents. Specifically, we find that the majority of individuals search for a job similar to their current or previous job (79% of employed and 72% of unemployed) and that women search for a job in lower-wage occupations—measured by the median occupation wage— which mimics the gender gap in past and current occupation wages (Table A.4).

Figure 1: Gender Expectations Gap

(a) Non-employed (b) Employed



Notes: Panels (a) and (b) display estimates of β from Equation 7 for non-employed and employed respondents, respectively. *Number of offers* represents the number of job offers respondents expect to receive in the next four months. *Best* and *average wage offer* refer to the highest and average hourly wage offers expected in the same period. *Separation likelihood* captures the perceived probability of being unemployed four months from now. All specifications include age and its square, duration of unemployment (Panel (a)) or employment (Panel (b)), a measure of ability, dummy variables for education, race, ability, whether she/he is married/lives with a partner or not, whether she/he has a child, whether an individual is searching for a job or not, state and survey date fixed effects. Panel (a) also controls for the wage in the previous job and panel (b) includes industry-fixed effects and the current wage. Shaded areas correspond to 95% confidence intervals using robust standard errors clustered at the individual level. The sample is a sub-sample from SCE subject to the criteria described in the main text, covering the period from November 2015 to November 2019.

Reservation Wage Gap According to the model in Section 2, labor market beliefs affect accepted wages through reservation wages. To test this prediction, we estimate a version of Equation 7 using the elicited reservation wages for the non-employed as an outcome variable. Column 1 shows that there is a gender difference in reservation wages, with women reporting, on average, reservation earnings that are about 18% lower than those of men. This difference is statistically significant at the 1% level and aligns with prior studies (e.g., Krueger and Mueller, 2016; Barbanchon et al., 2020). Column 2 shows a positive correlation between expectations and reservation wages. Notably, when including expectations about job offers and the highest potential wage offer, the gender gap in reservation wages narrows to 6%, accounting for approximately 64% of the original difference. The final two columns confirm that this result is not confounded by gender differences in risk aversion.[8] As expected, risk tolerance is positively correlated with the reservation wage (Cortés et al., 2023), explaining around 11% of gender differences in the reservation wage.

[8] To measure risk aversion, we leverage on two questions from the SCE survey: *(i)* "*On a scale from 1 to 7, how would you rate your willingness to take risks regarding financial matters?*"; and *(ii)* "*More generally, how would you rate your willingness to take risks in daily activities?*". Both questions are measured on a scale from 1 "not willing at all" to 7 "very willing". Figure A.1 plots the distribution of risk tolerance for men and women separately. The men's distribution is generally to the right of the women's distribution, suggesting that women tend to be more risk-averse than men. If we take the simple average of the two responses, we observe a raw difference in risk tolerance between women and men of -0.45. This pattern is in line with a large experimental literature showing a robust difference in risk preferences between men and women, with women showing a greater degree of risk aversion (Croson and Gneezy, 2009). In the regression, we include the simple average of the two responses. The results are unchanged if we include each measure separately.

Taken together, these findings highlight the importance of job search expectations and their potential role in shaping the gender gap in labor market outcomes through their influence on reservation wages.

Table 2: Reservation Wage Gap

	(1)	(2)	(3)	(4)
female	-0.176***	-0.063*	-0.156***	-0.049
	(0.050)	(0.035)	(0.051)	(0.035)
expected best wage offer		0.645***		0.643***
		(0.035)		(0.035)
expected offers		0.009		0.007
		(0.012)		(0.012)
risk tolerance			0.037**	0.028**
			(0.019)	(0.012)
Observations	929	929	929	929

Notes: The table reports coefficients from OLS regressions with robust standard errors clustered at the individual level. The dependent variable is the log of the hourly reservation wage. All columns include age and its square, duration of unemployment , hourly wage in the previous job, a measure of ability, dummy variables for education, race, ability, whether they are married/lives with a partner or not, have a child or are searching for a job, state and survey date fixed effects. *risk tolerance* is the simple average of the responses to the two questions measuring risk preference available at SCE, as described in the main texts. The sample is a sub-sample from SCE subject to the criteria described in the main text, covering the period from November 2015 to November 2019. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Robustness Checks Figure A.2, Figure A.3 and Figure A.4 in Appendix A confirm the robustness of the documented findings. First, the results hold with additional controls, including non-wage job amenities, job search intensity (hours searched in the past 7 days), past job offers (last 4 months), and industry (for the non-employed).[9] Second, the findings hold when we adopt narrower definitions of non-employment (e.g., CPS-defined job seekers or those with a positive likelihood of working within 4 months) yields similar results. Finally, when we distinguish between short-term ($\leq$2 years) and long-term (>2 years) non-employed individuals, we observe a larger reservation wage gap for the long-term group. However, expectations still account for a substantial portion of the gap in both cases.

3.2 Structural Assumptions

This subsection describes the mapping between a worker's type x_i and the model parameters. When estimating the model, a worker's type x_i is defined by a vector of observable characteristics which

[9]Job non-wage amenities are a set of categorical variables that equal 1 if the employer (current/previous) provided the following benefits: (i) traditional pension plans, (ii) contribution to a retirement account, (iii) health insurance, (iv) dental or vision insurance, (v) housing or housing subsidy, (vi) life or disability insurance, (vii) commuter benefits and (viii) childcare assistance.

include: age (and its square), indicators for education, race, ability, marital or partnership status, presence of children, and job search status. We omit the subscript $g \in \{f, m\}$ to simplify notation, keeping in mind that model parameters are gender specific.

Job arrival rates We assume that the number of believed and true job offers in both unemployment ($l = u$) and employment ($l = e$) follow a Poisson distribution, with believed arrival rate $\lambda_l^B(x_i)$ and true arrival rate $\lambda_l(x_i)$, respectively. We consider that both arrival rates depend on individual i's type x_i as well as an unobservable error term. Thus, the believed and true arrival rates of job offers are given by

$$\lambda_l^B(x_i) = \nu_{l,i}^B \cdot \exp(\beta_{\lambda_l^B} \cdot x_i), \tag{8}$$

$$\lambda_l(x_i) = \nu_{l,i} \cdot \exp(\beta_{\lambda_l} \cdot x_i) \tag{9}$$

where $\nu_{l,i}^B \sim Gamma\big(k_{\nu_l^B}, \theta_{\nu_l^B}\big)$ and $\nu_l \sim Gamma\big(k_{\nu_l}, \theta_{\nu_l}\big)$, with $l \in \{u, e\}$. This implies that conditional on worker type x_i, both the believed and true arrival rates follow a Gamma distribution, $\lambda_l^B|x_i \sim Gamma\big(k_{\nu_l}^B, \theta_{\nu_l}^B \cdot \exp(\beta_{\lambda_l^B} \cdot x_i)\big)$ and $\lambda_l|x_i \sim Gamma\big(k_{\nu_l}, \theta_{\nu_l} \cdot \exp(\beta_{\lambda_l} \cdot x_i)\big)$, respectively. Therefore, both the expected and received number of offers follow a negative binomial distribution.[10]

Wage offer distributions We assume that, for an individual of type x_i, the believed and true wage offer in logs are given by

$$\ln w_i^B = c_{\mu^B} + \beta_{\mu^B} \cdot x_i + \varepsilon_i^B, \tag{10}$$

$$\ln w_i = c_\mu + \beta_\mu \cdot x_i + \varepsilon_i \tag{11}$$

where $\varepsilon_i^B \sim N(0, \sigma^B)$ and $\varepsilon_i \sim N(0, \sigma)$. Therefore, the believed wage offer follows a log-normal distribution, $w_i^B \sim \ln N(\mu_i^B, \sigma^B)$, with cumulative density function denoted by $G^B(w_i^B; \mu_i^B, \sigma^B)$, where $\mu_i^B = c_{\mu^B} + \beta_{\mu^B} \cdot x_i$. Similarly, the true wage offer follows a log-normal distribution, $w_i \sim \ln N(\mu_i, \sigma)$, with cumulative density function denoted by $G(w_i; \mu_i, \sigma)$, where $\mu_i = c_\mu + \beta_\mu \cdot x_i$.

Separation rates While on-the-job, a worker of type x_i perceives separations to occur at a Poisson rate δ_i^B, while actual separations occur at a Poisson rate δ_i. We assume both depend on the vector of observable characteristics x_i and an error term. As such, the believed and true rate of job separation rates are given by:

$$\delta_i^B = \phi_i^B \cdot \exp(\beta_{\delta^B} \cdot x_i) \tag{12}$$

$$\delta_i = \phi_i \cdot \exp(\beta_\delta \cdot x_i), \tag{13}$$

[10] Appendix C.1 provides the derivation of these distributions.

where $\phi_i^B \sim Gamma(k_{\phi^B}, \theta_{\phi^B})$ and $\phi_i \sim Gamma(k_\phi, \theta_\phi)$.

3.3 Likelihood Function

We now discuss the likelihood function, starting with the contributions of unemployed and employed workers. We assume that all error terms are independent, $\nu_{l,i}^B \perp \nu_{l,i} \perp \varepsilon_i \perp \varepsilon_i^B \perp \phi_i^B \perp \phi_i$, with $l = \{u, e\}$. This implies that conditional on observable characteristics, the errors in reported wages, arrival, and separation rates are independent. Appendix C.1 outlines functional forms of all the following probability density functions.

Unemployed Worker Let $p_{u,i}$ be the probability that an unemployed individual of type x_i expects to receive at least one offer, $n_{u,i}^B$ be the number of offers they expect to receive, and $\bar{w}_i^B$ the highest expected wage offer. Additionally, let $n_{u,i}$ represent the true number of offers received, with $w_{1,i} \geq w_{2,i} \geq w_{3,i}$ as the top three offers received. The probability of observing an individual with $p_{u,i}$, $n_{u,i}^B$, $\bar{w}_i^B$, $n_{u,i}$ and the set $\tilde{w}_i = \{w_{1,i}, w_{2,i}, w_{3,i}\}$, conditional type x_i and unemployment status is given by

$$\begin{aligned} P(p_{u,i}, n_{u,i}^B, \bar{w}_{u,i}^B, n_{u,i}, \tilde{w}_i | x_i, u_i) =& [P(p_{u,i} > 0 | x_i, u_i) P(n_{u,i}^B | p_{u,i}, x_i, u_i) P(\bar{w}_{u,i}^B | p_{u,i}, n_{u,i}^B, x_i, u_i)]^{\mathbb{1}(p_{u,i}>0)} \\ & \times P(p_{u,i} = 0 | x_i, u_i)^{\mathbb{1}(p_{u,i}=0)} \times P(n_{u,i} = 0 | x_i, u_i)^{\mathbb{1}(n_{u,i}=0)} \\ & \times [P(w_{i,1} | n_{u,i} = 1, x_i, u_i) P(n_{u,i} = 1 | x_i, u_i)]^{\mathbb{1}(n_{u,i}=1)} \\ & \times [P(w_{1,i}, w_{2,i} | n_{u,i} = 2, x_i, u_i) P(n_{u,i} = 2 | x_i, u_i)]^{\mathbb{1}(n_{u,i}=2)} \\ & \times [P(w_{1,i}, w_{2,i}, w_{3,i} | n_{u,i} \geq 3, x_i, u_i) P(n_{u,i} \geq 3 | x_i, u_i)]^{\mathbb{1}(n_{u,i}\geq 3)}, \end{aligned} \tag{14}$$

where the joint probabilities can be separated by the assumption of independent errors.

Employed Worker Let $p_{e,i}$ represent the probability that an employed individual of type x_i expects to receive at least one offer, $n_{e,i}^B$ the number of offers they expect to receive, $\bar{w}_i^B$ the highest expected wage offer. Let $n_{e,i}$ be the true number of offers received, with $w_{1,i} \geq w_{2,i} \geq w_{3,i}$ as the top three offers received. Additionally, let d_i denote the observed employment duration of worker i, w_i^c the current wage, and s_i^B the perceived separation probability. The probability of observing an individual with $p_{e,i}$, $n_{e,i}^B$, $\bar{w}_i^B$, $n_{e,i}$, $\tilde{w}_i$, d_i, w_i^c, s_i^B, conditional on their type x_i and being employed is given by

$$
\begin{aligned}
P(p_{e,i}, n^B_{e,i}, \bar{w}^B_{e,i}, n_{e,i}, \tilde{w}_i, d_i, w^c_i | x_i, e_i) = &\\
& [P(p_{e,i} > 0 | x_i, e_i) P(n^B_{e,i} | p_{e,i}, x_i, e_i) P(\bar{w}^B_{e,i} | p_{e,i}, n^B_{e,i}, x_i, e_i)]^{\mathbb{1}(p_{e,i} > 0)} \\
& \times P(p_{e,i} = 0 | x_i, e_i)^{\mathbb{1}(p_{e,i} = 0)} \times P(n_{e,i} = 0 | x_i, e_i)^{\mathbb{1}(n_{e,i} = 0)} \\
& \times [P(w_{i,1} | n_{e,i} = 1, x_i, e_i) P(n_{e,i} = 1 | x_i, e_i)]^{\mathbb{1}(n_{e,i} = 1)} \\
& \times [P(w_{1,i}, w_{2,i} | n_{e,i} = 2, x_i, e_i) P(n_{e,i} = 2 | x_i, e_i)]^{\mathbb{1}(n_{e,i} = 2)} \\
& \times [P(w_{1,i}, w_{2,i}, w_{3,i} | n_{e,i} \geq 3, x_i, e_i) P(n_{e,i} \geq 3 | x_i, e_i)]^{\mathbb{1}(n_{e,i} \geq 3)} \\
& \times P(d_i | w^c_i, x_i, e_i) P(w^c_i | x_i, e_i) \times P(s^B_i | x_i, e_i), \qquad (15)
\end{aligned}
$$

where the joint probabilities can be separated by the assumption of independent errors.

Complete Likelihood Function The complete log-likelihood function for the entire sample of size N is given by:

$$
\begin{aligned}
\ln \mathcal{L} = \sum_{i=1}^{N} & \mathbb{1}(u_i = 1) \times [\ln P(p_{u,i}, n^B_{u,i}, \bar{w}^B_{u,i}, n_{u,i}, \tilde{w}_i | x_i, u_i) + \ln P(u_i | x_i)] \\
& + \mathbb{1}(u_i = 0) \times [\ln P(p_{e,i}, n^B_{e,i}, \bar{w}^B_{e,i}, n_{e,i}, \tilde{w}_i, d_i, w^c_i | x_i, e_i) + \ln P(e_i | x_i)], \qquad (16)
\end{aligned}
$$

where u_i is an indicator variable that takes on the value 1 if the worker is unemployed and 0 otherwise, and $e_i = 1 - u_i$. By maximizing Equation 16, we estimate the coefficients associated with each covariate in the functional forms for the believed and true job arrival rates $(\beta_{\lambda^B_l}, \beta_{\lambda_l}$, where $l = \{u, e\}$, in Equation 8$)$, the believed and true job separation rates $(\beta_{\delta^B}, \beta_\delta$ in Equation 12$)$, and the mean of the believed and true wage offer distributions $(\beta_{\mu^B}, \beta_\mu$ in Equation 10$)$. We also estimate the parameters governing the distribution of the error terms $(k_{\nu^B_l}, \theta_{\nu^B_l}, k_{\nu_l}, \theta_{\nu_l}, \sigma^B, \sigma, k_{\phi^B}, \theta_{\phi^B}, k_\phi, \theta_\phi$, where $l = \{u, e\})$. All parameters are estimated separately for men and women, making them specific to gender and type x_i. For the estimation, we residualized the believed wage offer, the wage offers received, and the reservation wage from the effects of commuting zone, industry and its interaction with education, and employment/unemployment duration. Columns 1 to 8 of Table C.1 and Table C.2 in Appendix C.2 report, for women and men respectively, the estimated parameters that determine believed and true job arrival rates, separation rates, and the wage offer distribution.

3.4 Flow value of Unemployment

For each respondent, we observe the reported reservation wage, $R(x_i)$, the believed job arrival rates, $\hat{\lambda}^B_u(x_i) = \mathbb{E}[\lambda^B_u | x_i]$ and $\hat{\lambda}^B_e(x_i) = \mathbb{E}[\lambda^B_e | x_i]$; the believed wage offer distribution, $\hat{G}^B_i \sim \ln N(\hat{\beta}_2 \cdot x_i, \hat{\sigma}^B)$; and the believed separation rate, $\hat{\delta}^B(x_i) = \mathbb{E}[\delta^B | x_i]$. Using this information, we calculate the flow value of unemployment of each worker type x_i as the residual between their reported reservation wage and the reservation wage predicted by the model. According to Equation 3, the estimated flow value of unemployment for worker type x_i, $\hat{b}(x_i)$, is given by

$$\hat{b}(x_i) = R(x_i) - \left[\hat{\lambda}_u^B(x_i) - \hat{\lambda}_e^B(x_i)\right] \int_{R(x_i)}^{\bar{w}} \frac{1 - \hat{G}^B(w|x_i)}{r + \hat{\delta}^B(x_i) + \hat{\lambda}_e^B(x_i)[1 - \hat{G}^B(w|x_i)]} \, dw. \tag{17}$$

We then assume that the worker type x_i and an unobservable error term, $\xi \sim N(0, \sigma_\xi^B)$, determine the flow value of unemployment linearly,

$$\hat{b}(x_i) = c_{\hat{b}} + \beta_{\hat{b}} \cdot x_i + \xi_i \tag{18}$$

and estimate the equation using OLS. Column 9 of Table C.1 and Table C.2 in Appendix C.2 presents the estimated coefficients, showing that individual characteristics are associated with the flow value of unemployment of men and women in a similar way.

4 Estimation Results

In this section, we present the estimation results, and the implied biases in labor market beliefs of the job arrival rates, the separation rate, and the wage offer distribution. Using the estimated model, we decompose the gender wage gap into components attributable to differences in observables, biased beliefs, and true labor market parameters.

4.1 Model Fit

Table 3 summarizes the fit of the model on reservation wages, wage offers, accepted wages, number of job offers, and employment durations. Overall, the model aligns well with the data. It matches closely gender differences in the reservation wage, and predicts a women-to-men wage ratio of 0.7, capturing around 94% of the ratio observed in the data (0.68). Although the model underestimates expectations about the number of job offers, it matches the actual number of offers received and the believed and true wage offer distributions well.

4.2 Estimated Biases in Labor Market Beliefs

Given our structural assumptions, model parameters—either believed or true values—may differ between men and women due to differences in their type, x_i, or in the estimated coefficients that discipline each parameter (Equations 7–12 and Equation 18). To isolate the effect of differences in observables between genders, we compute gender-specific model parameters by equalizing women's average characteristics to those of men. Let y^B be the believed counterpart of the true

Table 3: Model Fit

	Men		Women	
	Data	Model	Data	Model
Reservation wage	5.25	5.23	3.77	3.77
Expected wage offer (max)	10.21	10.07	7.20	6.81
Wage offered (max)	4.77	5.42	3.34	3.98
Expected job offers				
Unemployed	1.25	1.08	1.51	1.29
Employed	0.96	0.85	1.07	0.85
Received job offers				
Unemployed	0.15	0.16	0.22	0.23
Employed	0.42	0.36	0.37	0.35
Accepted wage	14.50	11.95	9.87	8.35
Employment duration	99.75	88.17	79.98	76.13

Notes: The table reports data and model moments for men and women, with values corresponding to the mean of each variable unless stated otherwise. Pay-related values—reservation wage, wage offers, and accepted wage—are residualized to account for differences in commuting zone, industry (and its interaction with education), and employment/unemployment duration. Employment duration is measured in months.

model parameter y, and let $\hat{\Omega}^g_{y^B}$ and $\hat{\Omega}^g_y$ be the set of estimated parameters governing y^B and y of gender g, respectively. We compute the average believed and true parameter, $\bar{y}^B_g$ and $\bar{y}_g$, using gender-specific estimated coefficients while holding the observables at the mean values for men, $\bar{x}_m$, for both genders:

$$\bar{y}^B_g = f\left(\hat{\Omega}^g_{y^B}, \bar{x}_m\right), \quad \bar{y}_g = f\left(\hat{\Omega}^g_y, \bar{x}_m\right), \quad \text{for } g \in \{f, m\}.$$

Table 4 presents the expected values of gender-specific model parameters, $\bar{y}^B_g$, and their true counterparts, $\bar{y}_g$, for each gender. It also reports the corresponding belief bias for each gender, as defined below.

Estimates of Model Parameters Columns 2 and 5 in Table 4 show our estimates of the *true* labor market parameters for both men and women $\left(\lambda_u, \lambda_e, \delta, \text{and the mean of } G(w)\right)$, respectively. Women receive fewer on-the-job offers and experience slightly higher separation rates, implying that they climb the job ladder at a slower pace. Men draw wage offers from a distribution with a higher mean. Columns 1 and 4 of Table 4 report estimates of labor market beliefs for men and women, respectively $\left(\lambda^B_u, \lambda^B_e, \delta^B, \text{and the mean of } G^B(w)\right)$. These beliefs largely align with true parameters. Men expect to receive more job offers, either when employed and unemployed, and believe to draw wage offers from a higher mean distribution than women. However, men expect the likelihood of losing a job to be higher. Overall, these gender differences in beliefs are consistent with the descriptive evidence in subsection 3.1.

Table 4: Biases in Labor Market Beliefs

	Men			Women		
	$\bar{y}^B$	$\bar{y}$	Bias	$\bar{y}^B$	$\bar{y}$	Bias
Offer arrival rate						
Unemployed	1.16	0.12	2.25	1.04	0.14	1.99
Employed	1.12	0.30	1.30	1.05	0.27	1.34
Wage offer distribution (mean)	8.00	4.79	0.51	6.47	4.05	0.47
Separation rate	0.19	0.04	1.56	0.16	0.05	1.23

Notes: The table reports estimated gender-specific model parameters—expected and true values—along with the corresponding belief biases for each gender. Column 1 (2) and 4 (5) show the average believed (true) model parameters, calculated using the gender-specific estimated coefficients and holding the observables constant at their mean values for men across both genders. Columns 3 and 6 report the estimated belief biases (Equation 19).

Estimates of Biases We define the bias in beliefs about a model parameter y for gender g, $bias_{y_g}$, as the log difference between the mean of the believed parameter $\bar{y}_g^B$ and its true counterpart $\bar{y}_g$, that is,

$$bias_{y_g} = \ln \bar{y}_g^B \left(\hat{\Omega}^g_{y^B}, \bar{x}_m\right) - \ln \bar{y}_g \left(\hat{\Omega}^g_y, \bar{x}_m\right), \tag{19}$$

where $\hat{\Omega}^g_{y^B}$ and $\hat{\Omega}^g_y$ are the set of estimated coefficients governing believed and true labor market parameters of gender g, respectively, and $\bar{x}_m$ the average observable characteristics of men. As such, any gender differences in estimated biases stem from differences in the estimated coefficients, not from observables.[11]

Columns 3 and 6 in Table 4 shows, for each gender, the bias in labor market beliefs implied by the model. Men and women are, on average, optimistic about the likelihood of receiving a job offer and the associated wages. When unemployed, they overestimate the job offer arrival rate, with men displaying a higher degree of optimism than women. Both also overestimate the mean of the wage offer distribution: the perceived mean is, on average, 51 log points higher than the actual mean, compared to 47 log points for women. In contrast, both men and women are pessimistic when it comes to job separation, that is, they tend to overestimate their risk of losing a job. This pessimism is greater for men, with a bias of about 1.56 log points, versus 1.23 for women.

4.3 Decomposition of the Gender Wage Gap

Based on the estimated parameters, we now analyze the drivers of the gender wage gap through the lens of the model, decomposing it into three components: (i) observables, (ii) biased beliefs, and (iii) true labor market parameters. The first two columns in Table 5 report the gender wage gap

[11] Details regarding the derivation of the bias for each model parameter are provided in Appendix C.3.

observed in the data and the one implied by the estimated model, where women and men differ both in observables, biased expectations, and true model parameters. We decompose the model-implied wage gap by sequentially eliminating each channel.

First, we equalize observables between men and women by setting $\bar{x}_f = \bar{x}_m$. This means we compute believed and true parameters using gender-specific estimated coefficients while keeping the observables fixed at men's average values for both genders. These are reported in Table 4. As a result, the gender pay gap declines by 10 percentage points, making observables responsible for around 1/3 of the wage gap (column 3 in Table 5). The remainder of the gap—henceforth, the 'residual gap'—is the part that cannot be explained by observable characteristics. In our setting, this may stem from gender differences in biased beliefs about labor market parameters or their true counterpart due to differences in the estimated coefficients that discipline each parameter.

Next, we measure the role of gender differences in expectations. To do so, we adjust women's expectations about model parameters so that their belief bias matches that of men, that is, we set $bias_{y_f} = bias_{y_m}$. Specifically, for a model parameter y, we set the log of women's average believed parameter y_f^B equal to the log of the average true parameter, computed using the estimated coefficients for women, $\hat{\Omega}_y^w$ keeping observables fixed at the average values for men, $\bar{x}_m$ (column 5 of Table 4), plus the estimated bias in men's beliefs (column 3 of Table 4):

$$\ln \hat{y}_f^B = \ln \bar{y}_f \left(\hat{\Omega}_y^w, \bar{x}_m\right) + bias_{y_m}. \tag{20}$$

As a result, the gender wage gap decreases by 6 percentage points, meaning that gender differences in biased expectations explain about 23% of the gender wage gap (column 4 in Table 5).

Finally, we evaluate the role of true labor market parameters. As shown in columns 2 and 5 of Table 4, women are more likely to fall off the job ladder and draw wages from a worst distribution. These differences in the latter may arise from various factors such as differences in bargaining (Card et al., 2016; Biasi and Sarsons, 2021; Roussille, 2022), taste-based discrimination (Becker, 1971; Flabbi, 2010), or gender-specific preferences for job attributes (Goldin, 2014; Morchio and Moser, 2024). While identifying the origins of these differences is beyond the scope of this paper, we investigate their role relative to beliefs in shaping gender inequality. To do so, we remove gender differences in true labor market parameters. Specifically, we set $\hat{\Omega}_y^f = \hat{\Omega}_y^m$ for each true model parameter y, such that $\bar{y}_f = \bar{y}_m$. This reduces the gender gap by 12 percentage points, implying that, all together, differences in true labor market parameters explain around 42% of the gender wage gap (column 5 in Table 5). The remaining small wage difference between men and women is due to differences in the estimated flow value of unemployment.

As an extension of our framework, we relax the assumption of risk neutrality and allow for differences in risk aversion between women and men. Specifically, we assume that workers'

Table 5: Decomposition of the Gender Wage Gap

	Data	Model	Observables	Biased Expectations	True Parameters	b-value
Wage Gap	31.90	28.65	18.64	12.19	0.11	0.00
Change			10.01	6.45	12.09	0.11
% explained			34.93	22.51	42.19	0.37

Notes: Table reports the decomposition of the model-implied ggender wage gap. The baseline economy (column 2) is compared to counterfactual scenarios without gender differences in observables, $\bar{x}_f = \bar{x}_m$ (column 3), without gender differences in biased beliefs, $bias_{y_f} = bias_{y_m}$ (column 4), without gender differences in true labor market parameters, $\hat{\Omega}_y^f = \hat{\Omega}_y^m$ (column 5), and without gender differences in flow values of unemployment (column 6). The wage gap is defined as $100 \cdot (1 - w_f/w_m)$, where w_f and w_m represent average wages of women and men, respectively. *Change* is the percent point change in the wage gap, and *% explained* the proportion of the wage gap explained by each channel.

instantaneous utility function is given by $u(y) = \frac{y^{1-\rho}-1}{1-\rho}$, where ρ is the coefficient of relative risk aversion. Risk aversion generally dampens the impact of expectation biases. This is because risk-averse workers are more likely to accept lower wages—that is, they have lower reservation wages—to avoid the uncertainty of prolonged unemployment. To explore this further, we conduct a counterfactual decomposition in which men and women have different levels of risk aversion, as estimated by Cortés et al. (2023). As expected, the contribution of biased expectations to the gender wage gap is reduced but remains substantial, explaining 15% of the gap, while differences in true labor market parameters account for 45%. Differences in risk aversion have a negligible effect, contributing only 0.26% to the gender wage gap (see Appendix D.1 for details about the calculations).

5 Counterfactual Analysis

In this section, we use the model to conduct two policy-relevant counterfactuals. First, we simulate an information intervention by making beliefs unbiased for men and women. An example of such a policy is pay transparency legislation, where firms are required to disclose information on pay potentially reducing biased beliefs. Second, given biased beliefs, we investigate the impact of equalizing women's true labor market parameters to those of men. We interpret this counterfactual as policies aimed at firms, such as equal pay mandates or gender quotas. Both counterfactuals abstract away from general equilibrium considerations as we assume that changing labor market beliefs does not change true parameters.[12] For each counterfactual, we compute average wages and welfare for men and women, focusing on the residual wage gap, which captures gender differences

[12] As discussed in Section 2, this assumption follows Table A.5, which shows that workers' expectations are not significantly correlated with job search effort in terms of applications sent. This suggests a rather weak link between workers' expectations and future realizations through search behavior. Similarly, Adams-Prassl et al. (2023) provides evidence that workers perceive a low return on additional hours of search, supporting the common practice of assuming constant job-finding rates.

after accounting for differences in observables (column 3 in Table 5). Results are summarized in Table 6. Column 1 shows the baseline residual wage and welfare gaps, columns 3 to 5 the unbiased beliefs counterfactual, and columns 6 to 9 the gender neutral labor market counterfactual.

Average Wage We compute the reservation wage for the average individual $\bar{x}_g$, $\tilde{R}(\bar{x}_g)$, using Equation 3 and counterfactual model parameters for men and women obtained from Equations 7–12 and Equation 18. Combining $\tilde{R}(\bar{x}_g)$ with Equation 6, we obtain the predicted average wage for men and women.

Welfare We define the gap in welfare between women and men as the percent change in men's lifetime consumption needed for them to have the utility level of their female counterparts, on average. Denoting the welfare for the average men W_m and W_f for women, the gender gap in welfare Λ is given by

$$\Lambda = \frac{W_f}{W_m} - 1 \tag{21}$$

The welfare functions W_m and W_f are the discounted sum of consumption for the average men and women of type $\bar{x}_g$, $W^g = U(R(\bar{x}_g))/r$, where

$$\begin{aligned} U(R(\bar{x}_g)) =& \frac{r + \delta(\bar{x}_g)}{r(r + \delta(\bar{x}_g) + \lambda_u(\bar{x}_g)[1 - F(R(\bar{x}_g))])} \Bigg(b(\bar{x}_g) + \lambda_u(\bar{x}_g) \int_{R(\bar{x}_g)}^{\infty} w \\ & + \lambda_e(\bar{x}_g) \int_{w}^{\infty} \frac{1 - F(w')}{r + \delta(\bar{x}_g) + \lambda_e(\bar{x}_g)[1 - F(w')]} \, dw' \, dw \Bigg), \end{aligned} \tag{22}$$

is the true value of unemployment at the worker's reservation wage calculated using Equation 3. The value of unemployment is maximized when the worker has biased beliefs about their labor market outcomes.

5.1 Unbiased Beliefs

Our first counterfactual removes the bias in beliefs about labor market parameters. This implies that we compute the reservation wage, as in Equation 3, using true labor market parameters rather than the worker's believed parameters. Column 2 of Table 6 reports the percentage change in wages and welfare relative to the baseline and the resulting gender gaps. Under unbiased beliefs, both men's and women's wages decrease, but the reduction is smaller for women, narrowing the wage gap by 2 percentage points. As workers recognize their outside option of search in unemployment to be worse due to lower true offer arrival rates while unemployed and a less favorable offer distribution, reservation wages decrease and job-finding rates increase. As a consequence, welfare improves for both genders but increases more for men, whose beliefs were more biased initially, resulting in a wider welfare gap.

Columns 3 to 5 show the effects of correcting biases separately for arrival rates (column 3), wage offer distribution (column 4), and separation rate (column 5). Addressing biases in offer arrival rates has the largest effect, narrowing the wage gap by 1.7 percentage points. This reduction stems from the realization that true offer arrival rates while unemployed are lower than expected, leading to a decrease in reservation wages. The effect is more pronounced for men, whose expectations are more optimistic. The decrease in reservation wages increases transitions out of unemployment and boosts welfare, but the gains are larger for men, further widening the welfare gap.

Column 4 presents the impact of correcting beliefs about the wage offer distribution, simulating interventions like pay transparency policies that require firms to disclose pay information. Consistent with empirical evidence (Gulyas et al., 2021; Duchini et al., 2022; Bennedsen et al., 2022), we find that such interventions have a modest effect on the gender pay gap, reducing it by around half a percentage point. The magnitude of the gender gap decrease in the model (0.43pp) is similar in size to the effect found by Bennedsen et al. (2022). The reduction is mainly driven by a decrease in men's reservation wages, as their beliefs about the wage offer distribution are further from the truth. Women's wages change only slightly, as their beliefs about job arrival rates while unemployed are similar to those when employed. As a consequence, the welfare gap widens. These results show that correcting workers' beliefs about the labor market has a limited impact on narrowing the wage gap and unintentionally widening the welfare gap between men and women, as men's initial biases are larger.

Table 6: Wage and Welfare Effects of Counterfactuals

	Baseline	Unbiased Beliefs				Equalized True Parameters			
		All	λ_u^B, λ_e^B	$G^B(w)$	δ^B	All	λ_u, λ_e	$G(w)$	δ
Wage									
Gap	18.64	16.57	16.99	18.12	18.92	7.15	22.88	5.39	16.97
Women (% Δ)		-2.56	-5.33	0.11	-0.04	14.13	-5.20	16.29	2.06
Men (% Δ)		-4.98	-7.22	-0.53	0.30				
Welfare									
Gap	4.39	4.85	4.77	4.49	4.33	-0.04	5.36	-0.95	4.17
Women (% Δ)		0.08	-0.05	-0.01	0.00	4.63	-1.02	5.58	0.23
Men (% Δ)		0.56	0.36	0.10	-0.06				

Notes: Table reports results from two counterfactual scenarios. Baseline wage and welfare gaps (column 1) are compared against the economy with unbiased beliefs (columns 2 to 5) and the economy where women's true labor market parameters are equal to those of men, while the bias in their beliefs remains unchanged. The wage gender gap is defined as $100 \cdot (1 - w_f / w_m)$, and the welfare gap is $100 \cdot -\Lambda$, where Λ is given by Equation 21. % δ is the percentage change in wages or welfare relative to the baseline.

5.2 Equalized Labor Market Parameters

Our second counterfactual eliminates gender differences in true labor market parameters by setting $\hat{\Omega}^f_y = \hat{\Omega}^m_y$ for each labor market parameter y, such that $\bar{y}_f = \bar{y}_m$. While doing so, we assume that the bias in women's beliefs remains constant. This requires adjusting women's believed parameters. Specifically, for each model parameter y, we compute a counterfactual believed parameter $\hat{y}^B_f$, in logs, as the average true parameter of men, $\bar{y}_m$, plus the estimated bias in women's beliefs relative to that parameter:

$$\ln \hat{y}^B_f = \ln \bar{y}_m \left(\hat{\Omega}^m_y, \bar{x}_m\right) + bias_{y_f}, \tag{23}$$

where $\bar{y}_m$ is the true parameter for the average man and $bias_{y_f}$ is the estimated bias in women's beliefs about parameter y, as defined by Equation 19.[13]

Column 6 of Table 6 shows that eliminating gender differences across all labor market parameters increases women's wages by 14%, narrowing the wage gap to 7.2%. It also raises women's welfare by 4.6%, closing the welfare gap completely. The key driver of this result is the wage offer distribution. Column 8 shows that equalizing the wage offer distribution increases women's wages by 16.3%, reduces the wage gap by 13 percentage points (71 percent of the baseline), and reverses the welfare gap, making women nearly 1% better off than men. In contrast, equalizing offer arrival rates increases the gender wage gap by 4 percentage points. As women are, on average, optimistic about the arrival of offers (Table 4), a higher offer arrival rate when employed boosts women's expectations. As a result, their perceived value of searching while unemployed decreases, leading to a lower reservation wage.

Taken together, our findings suggest that tackling gender disparities in the wage offer distribution is more effective in reducing gender inequality in both pay and welfare than policies focused on providing information about pay. In contrast, efforts to equalize hiring opportunities may have unintended consequences: as women adjust their expectations, they accept lower-paying jobs when unemployed, ultimately increasing the wage gap. **??** shows that the wage and welfare effects of the counterfactual experiments remain overall unchanged if we relax the assumption of risk neutrality.

5.3 Parenthood

Recent research highlights parenthood as a key factor in explaining the persistent gender pay gap (e.g. Kleven et al., 2019), largely driven by gender differences in labor supply along both extensive and intensive margins. For instance, after having children, women often prefer reduced hours, part-time work, and flexible schedules (Goldin, 2014). Thus, one might expect the relative contribution of biased expectations versus true labor market parameters to the gender wage gap may differ between

[13]Columns 3 and 6 in Table 4 report, respectively, $\bar{y}_m$ and $bias_{y_f}$ for each model parameter.

parents and non-parents. As we allow model parameters to vary within each gender as a function of observables, including whether they have children or not, our framework allows us to tackle this issue in a straightforward way. Specifically, we recompute average wages for men and women with and without children. To do so, we set the "child" dummy variable to either 1 (for parents) or 0 (for non-parents) while keeping all other variables fixed at their average values, and then adjust the model parameters accordingly. In what follows, we decompose wage differentials among parents and non-parents into components attributable to observables, biased beliefs, and true labor market parameters. We then simulate the same policy counterfactuals as outlined in Section 5.

Decomposition Table 7 summarizes the results of the wage gap decomposition. Columns 1 and 2 show the observed wage gap in the data and the model-implied wage gap, respectively. For non-parents, we find that the model fully explains the gender wage gap. However, as expected, for parents, the model accounts for only 80% of the pay difference between men and women with children, suggesting other factors at play. For example, our model does not capture wage disparities arising from differences in human capital accumulation related to fertility decisions, as highlighted by Xiao (2021).

Decomposition of the wage shows that observables contribute about one-third of the wage gap for both parents and non-parents. However, the roles of biased beliefs and labor market parameters vary significantly. For non-parents, biased beliefs account for around 34% of the wage gap, while labor market parameters contribute approximately 21%. In contrast, for parents, the gender wage gap is largely driven by differences in true labor market parameters. This suggests that policies targeting true labor market parameters may have a more substantial impact on the gender wage gap for individuals with children. To explore this further, we conduct the same policy-relevant counterfactuals as in Section 5.

Counterfactuals We now ask what would be the wage gap for parents and non-parents if (i) beliefs about the labor market were unbiased, and (ii) there were no gender differences in true labor market parameters. As in Section 5, we depart from the residual wage gap, that is, gender differences in pay after accounting for differences in observables (column 3 in Table 7). Table D.5 in Appendix D.2 reports average wages for parents and non-parents in each counterfactual.

When beliefs about labor market parameters are unbiased, the residual gender wage gap decreases by approximately 1 percentage point for non-parents and 2.5 percentage points for parents. This reduction is primarily driven by a larger decline in men's wages, as men exhibit stronger biases than women, both among non-parents and parents.[14] Among the different biases, correcting for biases in offer arrival rates has the largest effect. In the second counterfactual, where true labor market parameters are equalized by assigning women the same parameters as men, the gender wage

[14] Table D.4 in Appendix D.2 reports the estimated biases in labor market parameters for parents and non-parents.

Table 7: Decomposition of the Gender Wage Gap: Parents vs. Non-Parents

	Data	Model	Observables	Biased Expectations	True Parameters	b-value
Panel A: Non-Parents						
Wage Gap	27.28	28.17	18.38	8.73	2.82	0.00
% Explained			34.74	34.27	20.99	10.00
Panel B: Parents						
Wage Gap	37.54	29.98	19.93	20.54	-4.42	0.00
% Explained			33.52	-2.03	83.24	-14.73

Notes: Tables reports the decomposition of the model-implied gender wage gap for non-parents (Panel A) and parents (Panel B). The baseline economy (column 2) is compared to counterfactual scenarios without gender differences in observables, $\bar{x}_f = \bar{x}_m$ (column 3), without gender differences in biased beliefs, $bias_{y_f} = bias_{y_m}$ (column 4), without gender differences in true labor market parameters, $\hat{\Omega}^f_y = \hat{\Omega}^m_y$ (column 5), and without gender differences in flow values of unemployment (column 6). The wage gap is defined as $100 \cdot (1 - w_f/w_m)$, where w_f and w_m represent average wages of women and men, respectively. *% Explained* is the proportion of the model wage gap explained by each channel.

gap closes entirely for parents and decreases by approximately 30% for non-parents. For both groups, changing the wage offer distribution of women to that of men's has the largest effect, albeit the magnitude is larger for parents. Although our model does not allow one to identify the specific drivers of differences in the wage offer distribution, this finding supports the theory of compensating differentials (Rosen, 1986). Women, particularly after having children, may prioritize non-wage amenities, such as flexible work arrangements (Goldin, 2014), which could lead them to lower-wage jobs, consistent with findings by Morchio and Moser (2024).

The fact that equalizing true labor market parameters affects mothers and non-mothers differently suggests that such policies have implications for the motherhood penalty. In the estimated model, having children is associated with a 7.3% lower wages, conditional on observables. However, when women are given the men's wage offer distribution, average wages increase by 22% for mothers and 13.5% for non-mothers, effectively eliminating the motherhood penalty. By contrast, correcting biased beliefs has little impact on the motherhood penalty, as the wages of mothers and non-mothers decrease by similar magnitudes.

Table 8: Counterfactual Wage Gaps: Parents vs. Non-Parents

	Baseline	Unbiased Beliefs				Equalized True Parameters			
		All	λ^B_u, λ^B_e	$G^B(w)$	δ^B	All	λ_u, λ_e	$G(w)$	δ
Non-Parents	18.38	17.04	17.14	18.50	18.35	12.16	25.62	7.32	17.36
Parents	19.93	17.39	18.70	18.31	20.69	-4.68	17.62	2.25	16.90

Notes: Table reports the model-implied wage gap in counterfactual scenarios. Baseline wage and welfare gaps (column 1) are compared against the economy with unbiased beliefs (columns 2 to 5) and the economy where women's true labor market parameters are equal to those of men, while the bias in their beliefs remains unchanged. The wage gender gap is defined as $100 \cdot (1 - w_f/w_m)$.

6 Conclusion

This paper sheds light on the contribution of labor market beliefs to differences in pay between women and men. To do so, we incorporate subjective expectations into an otherwise standard model of the labor market with on-the-job search. In the model, biased beliefs affect wages through their impact on reservation wages. Using the Survey of Consumer Expectations, we provide evidence supporting this mechanism.

Our analysis shows that biased beliefs account for approximately 23% of the gender wage gap, while differences in true labor market parameters explain 42%. Interestingly, the role of biased beliefs varies by parenthood status: they play a significant role for non-parents but are negligible for parents. This suggests that assuming rational expectations may lead to misleading conclusions about the mechanisms behind the gender wage gap, particularly when studying early-career gender wage disparities. While correcting biased beliefs slightly reduces the wage gap, it unintentionally widens welfare differences. In contrast, equalizing women's true labor market parameters with those of men significantly reduces both pay and welfare disparities. Overall, the results suggest that beliefs are a driver of the gender wage and welfare gap, but policies aimed at increasing opportunities for women may achieve equality better than those aimed at aligning workers' beliefs.

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A Data Appendix

Table A.1: Descriptive Statistics: SCE - Labour Market Supplement vs CPS

Variable (mean)	SCE - LMS	CPS	p-value
Age (years)	45.9	44.3	0.808
Female	48.8	48.3	0.984
White	79.9	76.5	0.795
College Degree or More	40.2	36.4	0.876
Children (total)	0.86	0.87	0.986
Married/Partner	65.1	58.4	0.795

Notes: The table reports means for samples from the SCE and CPS monthly data from 2015 to 2019. Both samples are restricted to individuals between 20 and 65 years old. The SCE sample is also restricted to individuals without any missing variables, as described in the main text. To be comparable to the SCE, the CPS sample in Column 2 is restricted to household heads and the months of March, July and November. *Children* is the total number of children in the household. Regarding the marital status, the SCE asks ”*Are you currently married or living as a partner with someone?*”, CPS respondents are classified as married or living with a partner if they are ”Married, spouse present” and ”Married, spouse absent”, or if someone else in their household reported themselves as the head of household's ”Partner roommate” or ”Unmarried partner.”. Except when indicated, columns report % of total. Column 3 reports the p-value of the equality of the CPS (in column 2) and SCE (in column 1) means.

Table A.2: Descriptive Statistics: Women HH vs Women non-HH and MaMenles

Variable (mean)	Women HH	Women non-HH	Men
Panel A: Demographics			
Age	44.2	40.7	42
White	74.4	77	77.8
College Degree or More	36.2	35.3	31.8
# Children	1.0	.9	.8
Married/Has Partner	51.9	70.9	62.4
Panel B: Labor Market Outcomes			
Employed	68.8	66.1	79
Unemployed	3.0	2.7	3.4
Out of Labor Force	28.2	31.3	17.5
Full-time Worker	79.8	77.2	90.8
Hours worked, Full-time Worker	41.6	41.2	43.4
Hours worked, Full-time Worker	22.5	22.2	22.8

Notes: The table reports means for women that are household heads (column 1), women that are not household heads (column 2) and males (column 3) in the the CPS monthly data from 2015 to 2019. The sample is restricted to individuals between 20 and 65 years old.

Table A.3: Occupation Shares

(% of employed)

Occupation	Women HH	Women non-HH	Men
Office and Administrative Support	17.5	18.1	6.1
Management in Business, Science, and Arts	10.7	9.6	13.3
Healthcare Practitioners and Technicians	10.1	10.1	2.8
Sales Related	9.3	10.6	9.5
Education, Training, and Library	9.4	9.8	3

Notes: The table reports the percentage of women household heads (column 1), women that are not household-heads (column 2) and males that work in each major occupation category. The set of occupation categories correspond to the five occupations with the largest share of workers among women that are household heads. The sample is from CPS monthly data covering the period from 2015 to 2019 and restricted to individuals between 20 and 65 years old.

Table A.4: Median hourly wage in the SOC 2-digit occupation (log, real)

	non-employed		employed	
	search occ	past occ	search occ	current occ
female	-0.252*	-0.248*	-0.120**	-0.087*
	(0.128)	(0.141)	(0.047)	(0.047)
Demographics	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	110	110	446	446

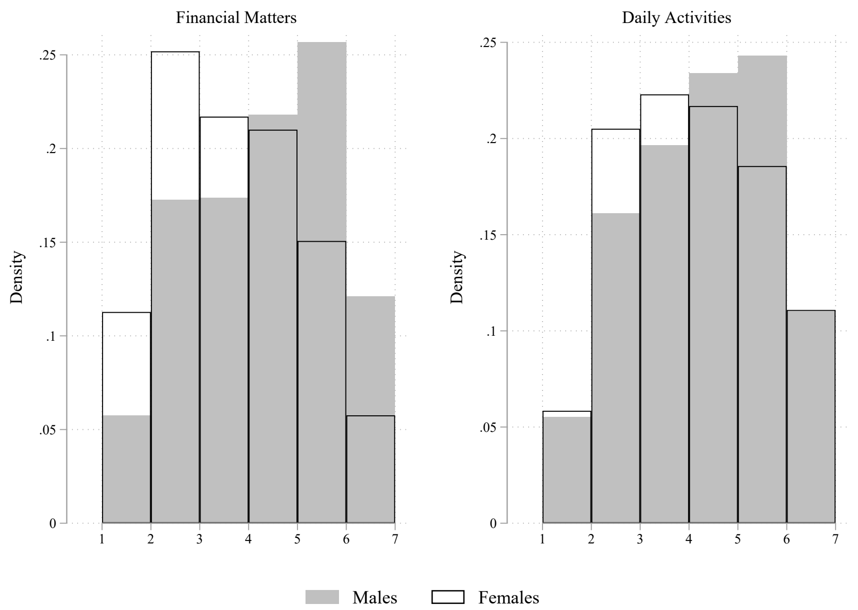
The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level. The dependent variable is the median hourly wage of the SOC 2-digit occupation individuals report to targeting in their job search. The median hourly wage for each SOC 2-digit occupation is computed CPS data. All columns include age and its square, dummy variables for education, race, whether she/he is married/lives with a partner or not, whether she/he has a child and survey date fixed effects. The sample is a sub-sample from the Job Search Supplement of the SCE subject to the criteria described in the main text, covering the period from 2015 to 2019. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table A.5: Expectations and Job Search Effort

	(1)	(2)	(3)	(4)	(5)
female	2.521	1.884	2.575	1.946	2.474
	(3.068)	(2.631)	(3.168)	(2.752)	(3.260)
exp. best offer		-2.402		-2.375	15.176
		(2.275)		(2.329)	(15.229)
exp. # offers			9.659	9.658	61.131
			(9.364)	(9.366)	(59.443)
Observations	1268	1268	1268	1268	1268

Notes: The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level. The dependent variable is the number of applications sent in the last 4 weeks, measured in October of a given year in the Job Search Supplement. The independent variables, expected number of offers and expected offered wage, are measured using information from prior Labor Market Supplements, conducted in July or March. All columns include age and its square,, a measure of ability, dummy variables for education, race, ability, whether she/he is married/lives with a partner or not, whether she/he has a child, an individual is searching for a job or not, whether an individual is employed or unemployed and survey date fixed effects. The sample is a sub-sample from SCE subject to the criteria described in the main text, covering the period from November 2015 to November 2019. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

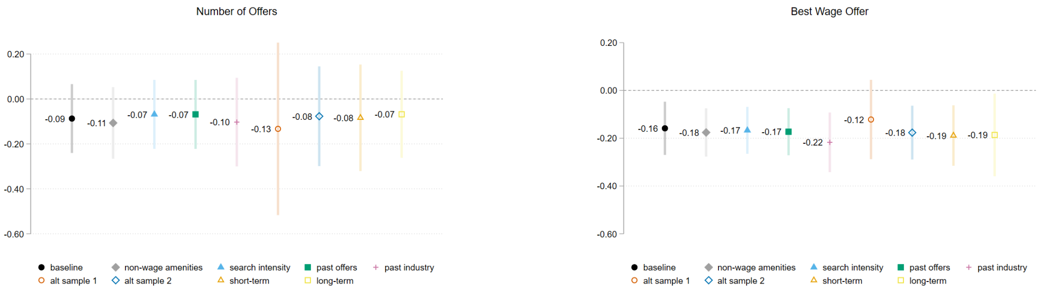
Figure A.1: Risk Tolerance: Women vs. Men



Notes: Panel A and B plots the distribution of risk tolerance in financial matters (left) and daily activities (right) for both genders. In the x-axis, 1 = not willing at all and 7 = very willing. The sample is a sub-sample from SCE subject to the criteria described in the main text, covering the period from November 2015 to November 2019.

Figure A.2: Gender Expectations Gap among the Non-employed: Robustness Checks

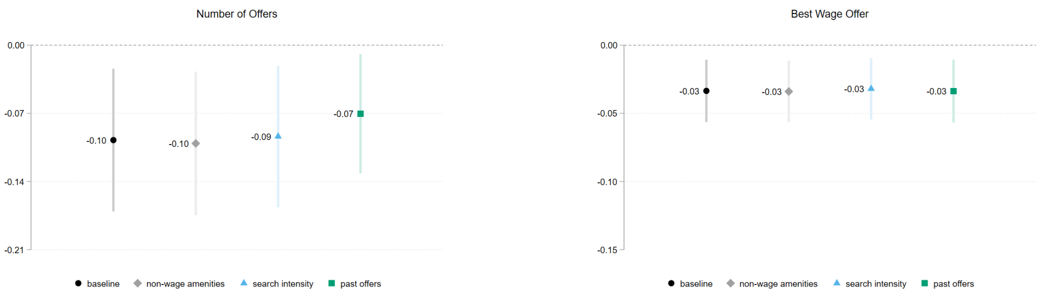
(a) Number of offers (b) Best wage offer



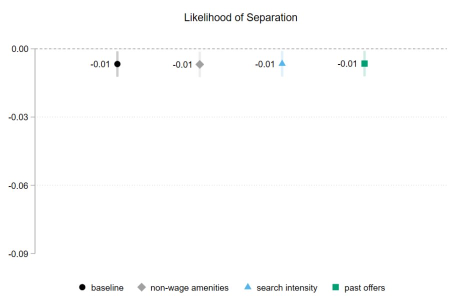
Notes: Figures replicate results in Figure 1a under different specifications: *non-wage amenities* includes a set of categorical variables that equal 1 if the employer provides the following benefits: (i) traditional pension plans, (ii) contribution to a retirement account, (iii) health insurance, (iv) dental or vision insurance, (v) housing or housing subsidy, (vi) life or disability insurance, (vii) commuter benefits and (viii) childcare assistance; *search intensity* controls for how many hours individuals search for a job in the past 7 days; *past offers* controls for the number of offers receive in past 4 months; *past industry* includes previous job's industry fixed effects; *alt sample 1* uses CPS-definition of job seekers without a job; *alt sample 2* focus on non-employed reporting a positive likelihood of working within 4 months; *short-* and *long-term* use a sample of short-term (≤2 years) and long-term (>2 years) non-employed individuals, respectively. The sample is a sub-sample from SCE subject to the criteria described in the main text, covering the period from November 2015 to November 2019.

Figure A.3: Gender Expectations Gap among the Employed: Robustness Checks

(a) Number of offers (b) Best wage offer



(c) Likelihood of Separation



Notes: Figures replicate results in Figure 1b under different specifications: *non-wage amenities* includes a set of categorical variables that equal 1 if the employer provides the following benefits: (i) traditional pension plans, (ii) contribution to a retirement account, (iii) health insurance, (iv) dental or vision insurance, (v) housing or housing subsidy, (vi) life or disability insurance, (vii) commuter benefits and (viii) childcare assistance; *search intensity* controls for how many hours individuals search for a job in the past 7 days; *past offers* controls for the number of offers received in past 4 months. The sample is a sub-sample from SCE subject to the criteria described in the main text, covering the period from November 2015 to November 2019.

Figure A.4: Reservation Wage Gap: Robustness Checks

(a) Not controlling for expectations

(b) Controlling for expectations

Notes: Panel (a) and (b) replicate, respectively, columns 3 and 4 in Table 2 under different specifications: *non-wage amenities* includes a set of categorical variables that equal 1 if the employer provides the following benefits: (i) traditional pension plans, (ii) contribution to a retirement account, (iii) health insurance, (iv) dental or vision insurance, (v) housing or housing subsidy, (vi) life or disability insurance, (vii) commuter benefits and (viii) childcare assistance; *search intensity* controls for how many hours individuals search for a job in the past 7 days; *past offers* controls for the number of offers receive in past 4 months; *past industry* includes previous job's industry fixed effects; *alt sample 1* uses CPS-definition of job seekers without a job; *alt sample 2* focus on non-employed reporting a positive likelihood of working within 4 months; *short-* and *long-term* use a sample of short-term (≤2 years) and long-term (>2 years) non-employed individuals, respectively. The sample is a sub-sample from SCE subject to the criteria described in the main text, covering the period from November 2015 to November 2019.

B Model Appendix

In steady state, the observed wage distribution for each worker type x_i does not change, $\frac{\partial F(w,t|x_i)}{\partial t} = 0$. This implies that

$$\lambda_u(x_i)[G(w|x_i) - G(R(x_i)|x_i)]u(x_i) = [\delta(x_i) + \lambda_e(x_i)[1 - G(w|x_i)]]F(w,t|x_i)(1 - u(x_i)), \quad \text{(B.1)}$$

where the left-hand side is the inflow of workers of type x_i to employment at jobs paying less than or equal to w at time t and the right-hand side is the outflow of workers from employment at jobs paying less than or equal to w at time t through either exogenous destruction or moving up the job ladder. Solving for $F(w|x_i)$, we obtain the cumulative distribution function (cdf) of the observed wage distribution, conditional on the worker's characteristics:

$$F(w|x_i) = \frac{\delta(x_i)[G(w|x_i) - G(R(x_i)|x_i)]/[1 - G(R(x_i)|x_i)]}{\delta(x_i) + \lambda_e(x_i)[1 - G(w|x_i)]} \quad \text{(B.2)}$$

Taking the derivative of the cdf yields the steady-state probability density function (pdf) of the observed wage distribution, conditional on the worker's characteristics:

$$f(w|x_i) = \frac{\delta(x_i)g(w|x_i)}{1 - G(R(x_i)|x_i)}\left[\frac{\delta(x_i) + \lambda_e(x_i)[1 - G(R(x_i)|x_i)]}{\{\delta(x_i) + \lambda_e(x_i)[1 - G(w|x_i)]\}^2}\right]. \quad \text{(B.3)}$$

The observed wage distribution for workers of type x_i has support $[R(x_i), \infty)$ where the upper limit is not defined in the partial equilibrium model but rather a result of the estimation assumptions. The mean of the observed wage is

$$\mathbb{E}_f[w|x_i] = \int_{R(x_i)}^{\infty} w f(w|x_i)\, dw$$

Substituting the pdf with Equation Equation B.3, we have

$$\mathbb{E}_f[w|x_i] = \frac{\delta(x_i)}{1 - G(R(x_i)|x_i)} \int_{R(x_i)}^{\infty} w g(w|x_i)\left[\frac{\delta(x_i) + \lambda_e(x_i)[1 - G(R(x_i)|x_i)]}{\{\delta(x_i) + \lambda_e(x_i)[1 - G(w|x_i)]\}^2}\right] dw. \quad \text{(B.4)}$$

C Estimation Appendix

C.1 Distributions Derivation

This section details the distributions used to construct the likelihood function, based on the structural assumptions, as outlined in Section 3.

Number of Offers We assume that, given the error term, the arrival rate of job offers follows a Poisson distribution, with the error term following a gamma distribution. Therefore, the probability of expecting to receive $n^B_{l,i}$ offers in labor market state $l \in \{u, e\}$ is given by

$$
\begin{aligned}
P(n^B_{l,i}|x_i) &= \int_0^\infty \frac{(\lambda^B_{l,i})^{n^B_{l,i}} \exp(-\lambda^B_{l,i})}{n^B_{l,i}!} \times f(\lambda^B_{l,i}|x_i)\, d\lambda^B_{l,i} \\
&= \int_0^\infty \frac{(\lambda^B_{l,i})^{n^B_{l,i}} \exp(-\lambda^B_{l,i})}{n^B_{l,i}!} \times \frac{(\lambda^B_{l,i})^{k^B_{\lambda,l}} \exp\left(\frac{-\lambda^B_{l,i}}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right)}{(\theta^B_{\lambda,l})^{k^B_{\lambda,l}} \exp(\beta^B_{l,1}x_i)^{k^B_{\lambda,l}} \Gamma(k^B_{\lambda,l})}\, d\lambda^B_{l,i} \\
&= \frac{1}{n^B_{l,i}!\Gamma(k^B_{\lambda,l})} \left(\frac{1}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right)^{k^B_{\lambda,l}} \int_0^\infty (\lambda^B_{l,i})^{n^B_{l,i}+k^B_{\lambda,l}-1} \exp\left[-\lambda^B_{l,i}\left(\frac{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right)\right] d\lambda^B_{l,i} \\
&= \frac{1}{n^B_{l,i}!\Gamma(k^B_{\lambda,l})} \left(\frac{1}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right)^{k^B_{\lambda,l}} \left(\frac{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right)^{n^B_{l,i}+k^B_{\lambda,l}} \Gamma(n^B_{l,i}+k^B_{\lambda,l}) \qquad \text{(C.1)} \\
&= \frac{\Gamma(n^B_{l,i}+k^B_{\lambda,l})}{n^B_{l,i}!\Gamma(k^B_{\lambda,l})} \left(\frac{1}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right)^{k^B_{\lambda,l}} \left(\frac{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right)^{n^B_{l,i}} \qquad \text{(C.2)}
\end{aligned}
$$

where Equation C.1 holds because $\int_0^\infty \lambda^a \exp(-b\lambda)\, d\lambda = \frac{\Gamma(a+1)}{b^{a+1}}$.

Given this, the number of job offers follows a negative-binomial distribution. The number of true arrivals is derived similarly. From Equation C.2, the probability that individual i believes they will have at least one offer is

$$
\begin{aligned}
P(p_{l,1} > 0|x_i) &= 1 - P(n^B_{l,1} = 0|x_i) \\
&= 1 - \left(\frac{1}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right), \qquad \text{(C.3)}
\end{aligned}
$$

and $P(p_{l,i} = 0|x_i) = 1 - P(p_{l,i} > 0|x_i)$.

Maximum Believed Wage Offer Since wages are an i.i.d. draw from the believed wage offer distribution G^B, the cdf of the expected maximum wage $\bar{W}^B_i$ conditional on $n^B_{l,i}$ expected offers and characteristics x_i is

$$
\begin{aligned}
P(\bar{W}^B_i \leq w|n^B_{l,i}, x_i) &= P(\max\{W^B_{i,1}, ..., W^B_{i,n^B_{l,i}}\} \leq w|n^B_{l,i}, x_i) \\
&= G^B(w; \mu^B_i, \sigma^B)^{n^B_{l,i}} \qquad \text{(C.4)}
\end{aligned}
$$

and the pdf is

$$P(\bar{w}_i^B|n_{l,i}^B, x_i) = n_{l,i}^B G^B(\bar{w}_i^B; \mu_i^B, \sigma^B)^{(n_{l,i}^B-1)} g^B(\bar{w}_i^B; \mu_i^B, \sigma^B) \tag{C.5}$$

where $\mu_i^B = c_2^B + \beta_2^B x_i$.

Observed Wage Offers Let $n_{l,i}$ the number of job offers received by worker i in employment state $l = \{u, e\}$ and let $w_{1,i} \geq w_{2,i} \geq w_{3,i}$ the top three offers received. The probability of observing a worker with these highest offered wages is $\tilde{w}_i = \{w_{1,i}, w_{2,i}, w_{3,i}\}$ conditional on $n_{l,i}$ offers is

$$\begin{aligned} P(\tilde{w}_i|n_{l,i}, x_i) = & [P(w_{1,i}|n_{l,i} = 1, x_i)P(n_{l,i} = 1|x_i)]^{\mathbb{1}(n_{l,i}=1)} \\ & \times [P(w_{i,1}, w_{2,i}|n_{l,i} = 2, x_i)P(n_{l,i} = 2|x_i)]^{\mathbb{1}(n_{l,i}=2)} \\ & \times [P(w_{1,i}, w_{2,i}, w_{3,i}|n_{l,i} \geq 3, x_i)P(n_{l,i} \geq 3|x_i)]^{\mathbb{1}(n_{l,i}\geq 3)}, \end{aligned} \tag{C.6}$$

Since wage offers are i.i.d draws from the offer distribution, conditional on receiving only one job offer, the probability of observing the offered wage $w_{i,1}$ is

$$P(w_{1,i}|n_{l,i} = 1, x_i) = g(w_{i,1}; \mu_i, \sigma) \tag{C.7}$$

where g is the pdf of G and $\mu_i = c_2 + \beta_2 x_i$. The probability of observing the offered wages $w_{i,1}$ and $w_{i,2}$ given only two offers is

$$P(w_{1,i}, w_{2,i}|n_{l,i} = 2, x_i) = g(w_{i,1}; \mu_i, \sigma) \times g(w_{i,2}; \mu_i, \sigma). \tag{C.8}$$

For workers with three or more wage offers, the probability of observing the best three offers is

$$P(w_{1,i}, w_{2,i}, w_{3,i}|n_{l,i} \geq 3, x_i) = (n_{l,i} - 2)G(w_{3,i}; \mu_i, \sigma)^{n_{l,i}-3} \prod_{j=1}^{3} g(w_{j,i}; \mu_i, \sigma). \tag{C.9}$$

Believed separation probability For employed workers, we observe their believed separation probability, $s_i^B \in [0, 1]$. We use this information as follows: if the worker reports $s_i^B = 0$, we include the observation in the likelihood function as the probability that no separation shock occured in the period, else if the worker reports $s_i^B > 0$ we include the observation in the likelihood function as the probability that the first shock will occur within the period. One period in the data is 4 month.

We have assumed the arrival rate of believed job separations is, conditional on the error term, Poisson, and that the error follows a gamma distribution. Therefore, the probability of expecting to receive n_s^B separation shocks follows a negative binomial distribution derived equivalently to job arrivals above. Then the probability of believing the separation probability to be 0 is

$$P(s_i^B = 0|x_i) = \left(\frac{1}{1+\theta_\delta^B \exp(\beta_3^B x_i)}\right)^{k_\delta^B}. \tag{C.10}$$

The probability of observing a positive separation probability is equal to the probability that the first separation shock will occur within the period. Since we assume separations follow a Poisson process, the arrival time of shocks is distributed exponentially, $s_i^B = 1 - \exp(-\delta_i^B)$. The cdf of the believed separation probability is

$$\begin{aligned} P(s_i^B \leq s|x_i) &= P[1-\exp(-\delta_i^B) \leq s] \\ &= P[1-\exp(-\phi_i^B \exp(\beta_3^B x_i)) \leq s] \\ &= P\left(\phi_i^B \leq \frac{-\ln(1-s_i^B)}{\exp(\beta_3^B x_i)}\right) \end{aligned} \tag{C.11}$$

Taking the derivative with respect to s_i^B and using the assumption that $\phi_i^B \sim Gamma(k_\delta^B, \theta_\delta^B)$ gives the pdf of the believed separation probability

$$p(s_i^B|x_i) = \frac{1}{\Gamma(k_\delta^B)[\theta_\delta^B \exp(\beta_3^B x_i)]^{k_\delta^B}} \frac{[-\ln(1-s_i^B)]^{k_\delta^B - 1}}{1-s_i^B} \exp\left(\frac{\ln(1-s_i^B)}{\theta_\delta^B \exp(\beta_3^B x_i)}\right). \tag{C.12}$$

For workers reporting $s_i^B = 1$, we subtract $2.2204e^{-16}$ so that Equation C.12 is real; 0.14% of the women sample and 0.45% of the men sample report a believed separation probability equal to 1.

Employment Duration The duration of an employment spell may end either by transitioning to a new job or through exogenous separation. Let the rate at which a worker leaves their current job be denoted by $\eta_i = \delta_i + \lambda_{e,i}[1 - G(w_i^c; \mu_i, \sigma)]$. Since separations to unemployment and transitions to a new employer follow independent Poisson processes, the overall rate η_i also follows a Poisson process. Since η_i is the sum of two independent gamma-distributed variables, we approximate η_i using the Welch-Satterthwaite approximation, yielding $\eta_i \sim_{approx} Gamma(k_\eta, \theta_\eta)$, where

$$k_\eta = \frac{\left(k_\delta\theta_\delta \exp(\beta_3 x_i) + k_{\lambda,e}\theta_{\lambda,e}\exp(\beta_{e,1}x_i)[1-G(w_i^c;\mu_i,\sigma)]\right)^2}{k_\delta\left(\theta_\delta \exp(\beta_3 x_i)\right)^2 + k_{\lambda,e}\left(\theta_{\lambda,e}\exp(\beta_{e,1}x_i)[1-G(w_i^c;\mu_i,\sigma)]\right)^2} \tag{C.13}$$

$$\theta_\eta = \frac{k_\delta\left(\theta_\delta \exp(\beta_3 x_i)\right)^2 + k_{\lambda,e}\left(\theta_{\lambda,e}\exp(\beta_{e,1}x_i)[1-G(w_i^c;\mu_i,\sigma)]\right)^2}{k_\delta\theta_\delta \exp(\beta_3 x_i) + k_{\lambda,e}\theta_{\lambda,e}\exp(\beta_{e,1}x_i)[1-G(w_i^c;\mu_i,\sigma)]}. \tag{C.14}$$

Given a single draw of η_i, the process for leaving the current employer follows a Poisson distribution, and the unconditional number of arrivals is negative binomial, as as previously shown. Thus, the probability of receiving no separation shocks (either to unemployment or new employment) over a duration t is

$$P(N_\eta(t) = 0|x_i) = \left(\frac{1}{1+\theta_\eta t}\right)^{k_\eta} \tag{C.15}$$

where $N_\eta(t)$ is the number of arrivals up to and including time t.

When an employment duration, d_i, is observed, it is a right-censored version of the full duration d_i^*. Therefore, the probability of observing an employment duration of length d_i is

$$P(d_i|w_i^c, x_i) = C[1 - P(N_\eta(d_i) = 0|x_i)] = C[1 - (1+\theta_\eta d_i)^{-k_\eta}] \tag{C.16}$$

where C is a constant such that the pdf integrates to one. Therefore,

$$C^{-1} = \int_0^\infty 1 - (1+\theta_\eta t)^{-k_\eta}\, dt = \frac{1}{\theta_\eta(k_\eta - 1)} \tag{C.17}$$

is the mean of a type II Pareto distribution. Altogether we have that the probability of observing the right censored employment duration, d_i is

$$P(d_i|w_i^c, x_i) = \theta_\eta(k_\eta - 1)[1+\theta_\eta d_i]^{-k_\eta}, \tag{C.18}$$

where k_η and θ_η are given by Equation C.13 and Equation C.14.

Current Wage Let w_i^c be the current wage of worker i. The probability that we observe this current wage follows the steady-state wage density F, that is,

$$P(w_i^c|x_i, e_i) = f(w_i^c|x_i, e_i) = \frac{\delta(x_i)g(w_i^c|x_i)}{1 - G(R_i|x_i)}\left[\frac{\delta(x_i) + \lambda_e(x_i)[1 - G(R_i|x_i)]}{\{\delta(x_i) + \lambda_e(x_i)[1 - G(w_c^i|x_i)]\}^2}\right]$$

where R_i is the reported reservation wage.

Unemployment and Employment Probability Let u_i be an indicator that equals 1 if worker i is unemployed and 0 otherwise, and let $e_i = 1 - u_i$. Then, in steady state the expected flow into and out of unemployment must be equal, that is

$$\mathbb{E}_\phi[\delta_i|x_i]P(u_i|x_i) = \{\mathbb{E}_\phi[\delta_i|x_i] + \mathbb{E}_\nu[\lambda_{u,i}][1 - G_i(R_i)]\}[1 - P(u_i|x_i)]. \tag{C.19}$$

Then the probability of observing worker i as unemployed is

$$P(u_i|x_i) = \frac{\mathbb{E}_\phi[\delta_i|x_i]}{\mathbb{E}_\phi[\delta_i|x_i] + \mathbb{E}_\nu[\lambda_{u,i}][1 - G_i(R_i)]} = \frac{k_\delta\theta_\delta \exp(\beta_3 x_i)}{k_\delta\theta_\delta \exp(\beta_3 x_i) + k_{\lambda,u}\theta_{\lambda,u}\exp(\beta_{u,1}x_i)[1 - G(R_i;\mu_i,\sigma)]} \tag{C.20}$$

and the probability of observing the worker as employed is $P(e_i|x_i) = 1 - P(u_i|x_i)$. During estimation, we set the probability of observing an unemployed and employed worker equal to the rates observed in our data, that is, $P(u_i|x_i) = 0.2655$ for women and $P(u_i|x_i) = 0.2026$ for men.

C.2 Parameter Estimates

Table C.1: Estimated Parameters for Women

	λ_u^B	λ_u	λ_e^B	λ_e	δ^B	δ	μ^B	μ	b
Age	0.050	-0.070	-0.011	-0.012	-0.157	-0.163	0.024	0.019	0.085
	(0.017)	(0.032)	(0.010)	(0.016)	(0.035)	(0.013)	(0.008)	(0.008)	(0.019)
Age^2	-0.001	0.001	0.000	0.000	0.002	0.002	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.106	0.284	-0.082	-0.274	-0.079	-0.121	0.213	0.184	0.537
	(0.065)	(0.262)	(0.035)	(0.071)	(0.091)	(0.046)	(0.023)	(0.023)	(0.177)
Child	0.033	0.126	0.082	0.282	0.512	0.031	-0.076	-0.105	-0.290
	(0.077)	(0.257)	(0.039)	(0.074)	(0.099)	(0.050)	(0.025)	(0.024)	(0.218)
Some College	0.031	0.352	-0.068	-0.015	0.397	0.019	-0.155	-0.403	-0.846
	(0.077)	(0.255)	(0.045)	(0.093)	(0.118)	(0.057)	(0.028)	(0.031)	(0.202)
College	0.018	0.932	-0.091	0.510	0.689	-0.052	0.279	0.424	0.793
	(0.088)	(0.273)	(0.049)	(0.098)	(0.134)	(0.063)	(0.034)	(0.032)	(0.263)
Advanced Degree	-0.162	-0.412	-0.054	0.563	-0.350	0.107	0.516	0.587	3.111
	(0.122)	(0.434)	(0.057)	(0.114)	(0.152)	(0.077)	(0.040)	(0.037)	(0.352)
Race-Black	0.471	0.456	0.243	0.188	-0.023	0.042	-0.129	-0.087	-0.389
	(0.086)	(0.335)	(0.053)	(0.109)	(0.143)	(0.074)	(0.030)	(0.037)	(0.250)
Race-Other	0.151	0.363	0.058	0.150	0.094	0.081	0.085	-0.008	-0.375
	(0.089)	(0.342)	(0.049)	(0.096)	(0.139)	(0.066)	(0.033)	(0.032)	(0.244)
High Ability	0.002	-0.081	-0.003	-0.261	0.196	-0.093	0.187	0.168	0.746
	(0.066)	(0.206)	(0.036)	(0.074)	(0.106)	(0.048)	(0.026)	(0.024)	(0.179)
Searching	0.877	1.384	0.870	0.668	0.079	0.338	-0.147	-0.126	-0.884
	(0.064)	(0.251)	(0.036)	(0.071)	(0.104)	(0.053)	(0.023)	(0.024)	(0.179)
Constant							0.807	0.614	0.112
							(0.155)	(0.157)	(0.046)
k	8.499	0.194	39.107	1.037	0.364	48.480			
	(2.315)	(0.031)	(47.858)	(0.041)	(0.016)	(64.531)			
θ	0.054	1.739	0.032	0.420	4.775	0.060			
	(0.023)	(1.127)	(0.040)	(0.148)	(3.503)	(0.086)			
σ							0.549	0.580	
							(0.009)	(0.007)	

Notes: table reports estimated coefficients for each observable characteristic, as well as parameters governing the respective error terms (when applicable) for the believed and true arrival rates when unemployed (columns 1 and 2) and when employed (columns 3 and 4), the believed and true arrival rates (columns 5 and 6), the wage offer distribution (columns 7 and 8) and the flow value of unemployment (columns 9). Standard errors are reported in parenthesis.

Table C.2: Estimated Parameters for Men

	λ_u^B	λ_u	λ_e^B	λ_e	δ^B	δ	μ^B	μ	b
Age	0.049	-0.137	0.025	0.046	-0.302	-0.116	0.049	0.021	0.064
	(0.019)	(0.038)	(0.030)	(0.024)	(0.026)	(0.016)	(0.008)	(0.012)	(0.022)
Age^2	-0.001	0.001	-0.000	-0.001	0.004	0.001	-0.001	-0.000	-0.000
	(0.001)	(0.007)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Married	0.094	0.499	-0.044	-0.160	0.093	-0.122	0.207	0.208	0.524
	(0.077)	(0.452)	(0.037)	(0.077)	(0.082)	(0.050)	(0.027)	(0.027)	(0.255)
Child	0.074	0.473	-0.037	-0.030	-0.367	-0.129	0.026	-0.017	-1.945
	(0.099)	(0.351)	(0.036)	(0.073)	(0.098)	(0.049)	(0.029)	(0.027)	(0.456)
Some College	0.142	1.109	0.078	-0.191	0.223	0.116	0.013	-0.269	-0.604
	(0.087)	(0.311)	(0.047)	(0.085)	(0.096)	(0.056)	(0.032)	(0.030)	(0.312)
College	0.165	1.368	0.058	-0.155	-0.107	0.142	0.455	0.563	1.430
	(0.100)	(0.414)	(0.046)	(0.082)	(0.098)	(0.058)	(0.033)	(0.030)	(0.402)
Advanced Degree	0.193	0.858	0.001	-0.010	-0.183	0.283	0.782	0.750	3.690
	(0.113)	(0.431)	(0.050)	(0.093)	(0.107)	(0.062)	(0.036)	(0.033)	(0.548)
Race-Black	0.319	1.002	0.335	0.519	-0.467	0.203	-0.117	-0.142	-0.469
	(0.124)	(0.422)	(0.069)	(0.128)	(0.181)	(0.095)	(0.045)	(0.047)	(0.494)
Race-Other	-0.276	-0.968	0.103	0.008	-0.027	0.077	-0.099	-0.099	2.296
	(0.136)	(0.541)	(0.047)	(0.093)	(0.109)	(0.059)	(0.034)	(0.034)	(0.572)
High Ability	-0.335	-0.788	0.028	-0.201	-0.152	-0.165	0.193	0.152	1.355
	(0.083)	(0.247)	(0.044)	(0.079)	(0.086)	(0.052)	(0.030)	(0.029)	(0.292)
Searching	0.805	1.309	0.681	0.741	-0.012	0.328	-0.173	-0.096	-1.608
	(0.079)	(0.324)	(0.035)	(0.066)	(0.092)	(0.054)	(0.024)	(0.024)	(0.294)
Constant							0.322	0.507	-0.094
							(0.174)	(0.203)	(0.049)
k	66.636	0.310	98.769	1.036	0.382	115.381			
	(33.356)	(0.072)	(50.010)	(0.036)	(0.015)	(58.244)			
θ	0.009	6.570	0.006	0.227	39.322	0.009			
	(0.003)	(2.742)	(0.003)	(0.094)	(20.617)	(0.005)			
σ							0.560	0.605	
							(0.012)	(0.010)	

Notes: table reports estimated coefficients for each observable characteristic, as well as parameters governing the respective error terms (when applicable) for the believed and true arrival rates when unemployed (columns 1 and 2) and when employed (columns 3 and 4), the believed and true arrival rates (columns 5 and 6), the wage offer distribution (columns 7 and 8) and the flow value of unemployment (columns 9). Standard errors are reported in parenthesis.

C.3 Derivation of Bias in Beliefs

We define the bias in beliefs about a model parameter y for gender g, $bias_{y_g}$, as the log difference between the mean of the believed parameter $\bar{y}_g^B$ and its true counterpart $\bar{y}_g$, that is,

$$bias_{y_g}(x_i) = \ln \bar{y}_g^B\big(\hat{\Omega}^g_{y^B}, x_i\big) - \ln \bar{y}_g\big(\hat{\Omega}^g_y, x_i\big), \tag{C.21}$$

where $\hat{\Omega}^g_{y^B}$ and $\hat{\Omega}^g_y$ are the set of estimated coefficients governing believed and true labor market parameters of gender g, respectively. In what follows, we provide details on how we compute the bias in beliefs about each parameter. All parameters are specific to the gender, therefore we suppress the subscript g for simplicity.

Job arrival and separation rates From Equation 8 and Equation 12, the bias in the log of arrival rates (λ_u and λ_e) and the log of separation rate (δ) for worker of type x_i is given, respectively, by

$$bias_{\lambda_l}(x_i) = (\hat{\beta}_{\lambda_l^B} - \hat{\beta}_{\lambda_l}) \cdot x_i + \ln \hat{k}^B_{\nu_l^B} - \ln \hat{k}_{\nu_l} + \ln \hat{\theta}_{\nu_l^B} - \ln \hat{\theta}_{\nu_l}, \; l \in \{u, e\} \tag{C.22}$$

$$bias_\delta(x_i) = \big(\hat{\beta}^B_{\delta^B} - \hat{\beta}_\delta\big) \cdot x_i + \ln \hat{k}_{\phi^B} - \ln \hat{k}_\phi + \ln \hat{\theta}_{\phi^B} - \ln \hat{\theta}_\phi \tag{C.23}$$

Offer distribution From Equation 10, the bias in the mean offer distribution is defined as

$$bias_\mu(x_i) = (\hat{c}_{\mu^B} - \hat{c}_\mu) + (\hat{\beta}_{\mu^B} - \hat{\beta}_\mu) \cdot x_i + \frac{(\sigma^B)^2}{2} - \frac{(\sigma)^2}{2}. \tag{C.24}$$

D Counterfactuals Appendix

D.1 Risk Aversion

In the baseline version of the model, both women and men are risk-neutral. As an extension of our framework, we relax the assumption of risk neutrality and allow for differences in risk aversion between women and men. Specifically, we assume that workers' instantaneous utility function is given by $u(y) = \frac{y^{1-\rho_g}-1}{1-\rho_g}$, where ρ_g is the coefficient of relative risk aversion, which we allow to vary by gender, $g \in \{f, m\}$. The believed value functions of the worker when unemployed and employed are now respectively given by

$$rU^B(x_i) = \frac{b(x_i)^{1-\rho}}{1-\rho} + \lambda_u^B(x_i) \int_{R(x_i)}^{\bar{w}} E^B(w, x_i) - U^B(x_i)\, dG^B(w|x_i), \tag{D.1}$$

$$rE^B(w, x_i) = \frac{w^{1-\rho}}{1-\rho} + \lambda^B(x_i) \int_{w}^{\bar{w}} E^B(w', x_i) - E^B(w, x_i)\, dG^B(w|x_i) + \delta^B(x_i)[U^B(x_i) - E^B(w, x_i)]. \tag{D.2}$$

For an unemployed worker, the reservation wage is defined as the wage offer which makes them indifferent between accepting and rejecting the offer, given their beliefs about the labor market, that is $E^B(R(x_i), x_i) = U^B(x_i)$, where $R(x_i)$ is the reservation wage. For worker of type x_i, the reservation wage is then given by:

$$R(x_i) = \left[b(x_i)^{1-\rho} + (1-\rho)[\lambda_u^B(x_i) - \lambda_e^B(x_i)] \int_{R(x_i)}^{\bar{w}} \frac{w^{-\rho}(1 - G^B(w|x_i))}{r + \delta^B(x_i) + \lambda_e^B(x_i)[1 - G^B(w|x_i)]}\, dw \right]^{\frac{1}{1-\rho}}. \tag{D.3}$$

The estimation strategy remains unchanged, with the estimates of all believed and true parameters—arrival rates, wage distributions, and separation rates—remaining the same. However, we now use Equation D.3 to estimate a new set of flow values for unemployment.

Different levels of risk aversion affect the decomposition and counterfactual exercises by altering how arrival rates, wage distributions, and separation rates impact the reservation wage. Table D.1 shows the effect of varying risk aversion, assuming both men and women have the same ρ. The first row shows the baseline model with risk neutrality, where biased expectations contribute 19% to the gender wage gap. As risk aversion increases, the contribution of biased expectations decreases, while the contribution of true parameters rises. From Equation D.3, it is clear that as $\rho \to 1$, changing beliefs has no effect on the reservation wage. Therefore, as workers become more risk-averse, the impact of expectation biases on the wage gap diminishes.

It is well-established that men and women have different attitudes toward financial risk (Eckel and Grossman, 2002; Charness and Gneezy, 2012). Therefore, we also compute the decomposition exercise and counterfactuals for the model with different values of ρ for men and women. Following Cortés et al. (2023), who estimate risk aversion among college graduates, we set $\rho = 0.5$ for men

Table D.1: Decomposition of the Gender Wage Gap and Risk Aversion

ρ	Model Wage Gap	Contribution from Observables	Biased Expectations	True Parameters	b-Values
0.00	28.65	34.93	22.51	42.19	0.37
0.10	29.83	32.32	20.01	40.41	7.27
0.25	29.64	32.58	18.60	42.04	6.78
0.50	29.76	32.42	16.22	43.71	7.65
0.75	29.94	32.00	14.17	44.85	8.98
0.90	30.03	31.80	13.12	45.46	9.62

Notes: Table reports the decomposition of the model-implied gender wage gap for different levels of relative risk aversion. Column 1 reports the wage gap in the baseline economy defined as $100 \cdot (1 - w_f/w_m)$, where w_f and w_m represent average wages of women and men, respectively. Columns 2 to 6 report the proportion of the model-implied wage gap explained by gender differences in observables (column 2), gender differences in biased beliefs (column 3), gender differences in true labor market parameter (column 4), and gender differences in flow values of unemployment (column 5)

and $\rho = 0.7$ for women. As before, the only estimated values that change are the b-values.

Table D.2 shows how the decomposition of the gender wage gap from the baseline to a model where men and women have different levels of risk aversion. Under risk neutrality (first row) biased expectation contributes 19% to the observed gender wage gap. As expected, since risk aversion dampens the effect of expectations, the contribution from biased expectations decreases, bur remains substantial, accounting for 15% of the observed wage gap.

Table D.2: Decomposition: Risk Neutrality vs. Gender Differences in Risk Aversion

	Model Wage Gap	Contribution from Observables	Biased Expectations	True Parameters	b-Values	ρ
Risk Neutral	28.65	34.93	22.51	42.19	0.37	0.00
Risk Aversion	29.73	32.35	14.67	45.02	7.70	0.26

Notes: Table reports the decomposition of the model-implied gender wage gap. Column 1 reports the wage gap in the baseline economy defined as $100 \cdot (1 - w_f/w_m)$, where w_f and w_m represent average wages of women and men, respectively. Columns 2 to 6 report the proportion of the model-implied wage gap explained by gender differences in observables (column 2), gender differences in biased beliefs (column 3), gender differences in true labor market parameter (column 4), gender differences in flow values of unemployment (column 5) and gender differences in risk aversion (column 6). *Risk Neutrality* corresponds to a model where workers are risk neutral. *Risk Aversion* corresponds to a model where women and men differ in their levels of relative risk aversion.

Table D.3 shows how risk aversion affects the counterfactuals in Section 5. Although the magnitude of the effects changes slightly with risk aversion, the overall conclusions remain: making workers unbiased in their beliefs does not affect the wage, but changing the true labor market conditions of women to reflect those of men can eliminate both the wage and welfare gaps.

Table D.3: Counterfactuals: Risk Neutrality vs. Gender Differences in Risk Aversion

	Wage Gap		Welfare Gap	
	Risk Neutral	Risk Averse	Risk Neutral	Risk Averse
Baseline	18.64	20.11	4.39	10.84
Unbiased Beliefs	16.57	18.65	4.85	11.06
Equalized True Parameters	7.15	6.67	-0.04	6.58

Notes: Table reports the model-implied wage gap in counterfactual scenarios. Baseline wage and welfare gaps (row 1) are compared against the economy with unbiased beliefs (row 2) and the economy where women's true labor market parameters are equal to those of men, while the bias in their beliefs remains unchanged (row 3). The wage gender gap is defined as $100 \cdot (1 - w_f/w_m)$, and the welfare gap is $100 \cdot -\Lambda$, where Λ is given by Equation 21.

D.2 Parenthood

Table D.4 reports the estimated biases in labor market parameters for parents and non-parents.Table D.5 shows average wages for parents and non-parents in the counterfactualS outline in Section 5.

Table D.4: Bias in Labor Market Beliefs: Parents vs. Non-Parents

	Non-Parents		Parents	
	Men	Women	Men	Women
Offer arrival rate				
Unemployed	1.99	1.92	2.39	2.02
Employed	1.29	1.20	1.30	1.40
Wage offer distribution (mean)	0.54	0.49	0.50	0.46
Separation rate	1.40	1.54	1.64	1.06

Notes: The table reports estimated gender-specific biases in beliefs about each model parameter for parents and non-parents.

Table D.5: Counterfactual Wages: Parents vs. Non-Parents

	Baseline	Unbiased Beliefs				Equalized True Parameters			
		All	λ_u^B, λ_e^B	$G^B(w)$	δ^B	All	λ_u, λ_e	$G(w)$	δ
Panel A: Non-Parents									
Women	8.67	8.43	8.19	8.66	8.67	9.33	7.90	9.84	8.78
Men	10.62	10.16	9.89	10.62	10.62				
Panel B: Parents									
Women	8.08	7.89	7.67	8.12	8.05	10.56	8.31	9.86	8.38
Men	10.09	9.55	9.44	9.94	10.15				

Notes: Table reports predicted average wages for men and women in counterfactual scenarios. Baseline average wages (column 1) are compared against the economy with unbiased beliefs (columns 2 to 5) and the economy where women's true labor market parameters are equal to those of men, while the bias in their beliefs remains unchanged (columns 6 to 9).