Labor Market Beliefs and the Gender Wage Gap

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Abstract

We study the role of labor market beliefs in the gender pay gap. We find that, on average, women expect to receive lower salaries than men and also expect to receive fewer offers when employed. Gender differences in expectations explain a sizable fraction of the residual gap in reservation wages. We estimate a partial equilibrium job search model that incorporates worker heterogeneity in beliefs about the wage offer distribution, arrival rates, and separation rate. Counterfactual exercises show that labor market beliefs play an important role in the gender wage gap, but matter little for the gender differences in welfare. Eliminating gender differences in the actual offer distribution, by contrast, decreases the gender gap in pay and welfare.

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1 Introduction

In the last decades, there was a remarkable convergence between women and men in labor force participation, occupational choices, and education. Nevertheless, gender differences in pay remain large, with women earning on average 25% less than (comparable) men (Goldin, 2014). This gap persists even when one accounts for differences in industry and occupation selection as well as education and labor market experience (Blau and Kahn, 2017). What can explain the remaining gender disparities in pay?

A growing literature has proposed differences in psychological traits (Bertrand, 2011), such as risk aversion (Cortés et al., 2021), propensity to negotiate (Biasi and Sarsons, 2021) or self-promotion (Exley and Kessler, 2022) as an explanation for women's lower wages . Relatedly, Reuben et al. (2017) and Bergerhoff et al. (2019) have shown that prior to entering the labor market women have lower salary expectations than (comparable) men. The implication of this finding for the observed gender gap in pay is yet unknown. This paper takes a first step in understanding how differences in expectations translate into actual wage differences between women and men.

Our contribution is twofold. First, we demonstrate that gender differences in expectations persist after entering the labor market and that they explain a substantial proportion of the observed gender gap in reservation wages. Second, we estimate a partial equilibrium job search model that incorporates heterogeneity in workers' beliefs and use it to quantify the importance of beliefs about the wage offer distribution, arrival rate, and separation rate in the observed gender gap in wage and welfare. In doing so, we show that beliefs drive differences in labor market earnings between women and men, but contribute little to differences in welfare. In contrast, equalizing labor market parameters such as the wage offer distribution brings large reductions in the gender gap in pay and welfare.

The analysis relies on a worker-level panel from the Survey of Consumer Expectations (CSE) supplemented by the Labor Market Supplement (LMS) covering the period from March 2015 to March 2019. We start by providing new evidence regarding gender differences in expectations about job offers and wages while searching for a job. We find that, while employed, women expect to receive fewer job offers than men, and that, regardless of their labor market status, women expect to receive lower salaries than men. In particular, the gap in expectations about the average wage offer is around 20% for employed workers and 27% for those unemployed. More importantly, we show that gender differences in wage expectations account for a sizeable share of the gender gap in reservation wages, reducing it to 17 percentage points for employed women and 11 percentage points for unemployed women. This result suggests that a worker's willingness to accept a job offer is one channel through which wage expectations affect actual wages. Finally, we provide suggestive evidence that workers are overly confident about the number of offers.

Building on these findings, we embed individual-level heterogeneity in beliefs in an otherwise standard model of the labor market with on-the-job search. Specifically, we allow workers to have biased beliefs about the job finding probability, separation probability, and future wage offers. In the model, beliefs affect realized wages through the reservation wage. We then structurally estimate the underlying process for believed and true job arrivals, wage offers, and job separations for men and women for workers in the LMS. The estimated model provides a good fit for the data, thus we use it to perform three counterfactual exercises that shed light on the sources of the gender differences in pay and welfare. These are partial equilibrium exercises in the sense that changing the beliefs of workers does not change the underlying true wage offer distribution or job arrival rates. Importantly, we show that this is consistent with the data.

In our first counterfactual exercise, we make women's beliefs about arrival rates, the wage offer distribution, and the separation rate as biased as those of men. In doing so, we find that the gap in the reservation wage gap and earnings decrease by nearly 3 and 2 percentage points, respectively, while the welfare gap remains unchanged. The reduction in gender disparities in pay is explained by beliefs about job arrival rates. Specifically, we show that if women and men are equally biased only in their beliefs about job arrival rates, the gender wage gap decreases by 23%, approximately.

We then conduct a counterfactual in which women's and men's beliefs are unbiased. We find that correcting workers' beliefs increases the reservation wage gap by 9 percentage points and the wage gap by 10 percentage points. The key driver is the fact that, when making beliefs unbiased, men's reservation wage increases more than the reservation wage of women due to changes in arrival rates that overturn the negative effect of correcting beliefs about the offer distribution. When we only correct beliefs about the wage distribution, mimicking an information shock such as pay transparency policies, the gender wage gap narrows down by 2.6 percentage points. This decrease is driven by a reduction in men's pay due to the fact that men's beliefs about the offer distribution are further away from the truth. Interestingly, our results are in line with empirical evidence on the effect of pay transparency policies (Bennedsen et al., 2022; Gulyas et al., 2021). Regarding gender, correcting beliefs also widens the welfare gap between men and women. This is because women's beliefs are less upward biased than those of men, and therefore men enjoy larger welfare gains when their beliefs are unbiased.

Finally, we investigate the role played by the true labor market parameters. If we set the women's true underlying parameters equal to those of men, i.e. same job arrival rates, separation rates, and offer distribution, while holding the bias in their beliefs unchanged, gender differences in earnings decrease by 6 percentage points, and in welfare by 15.8 percentage points. This reduction is driven by changes in women's offer distribution. When women receive offers from the same underlying offer distribution as men, while all other parameters remain unchanged, the gender wage gap decreases by 7 percentage points, and the welfare gap decreases by 7.5 percentage points.

Our results bring important insights into the ongoing debate about the reasons behind the gender wage disparity and the best policy instruments to close this gap. While we show that beliefs about the labor market are an important driver of gender differences in pay, policies aimed at changing beliefs are not successful in closing the gender gap in welfare. On the one hand, correcting biased beliefs widens the gender welfare gap as men enjoy larger welfare gains from having unbiased beliefs when compared to women. On the other hand, making women's beliefs as biased as those of men induces them to remain unemployed longer in hopes of better wages. This contrasts with policies aimed at giving women and men the same opportunities in the labor market, either by equalizing arrival rates or the wage offer distribution, which not only reduce gender differences in pay but also reduce gender differences in welfare.

Following recent literature that finds evidence the gender pay gap widens significantly after the birth of the first child (Chung et al., 2017; Kleven et al., 2019), we explore whether the role played by beliefs and true parameters in the gender wage gap differ depending on whether workers have children or not. We find that policies aimed at changing beliefs affect the search behavior of women without kids, reducing gender differences among individuals with no children, but have no impact on the gender gap among workers with children. Changes in the true labor market parameters also yield different reductions in pay and welfare depending on whether workers have children or not. While for workers with children, having the same labor market parameters as men decreases the gender wage gap by 8 percentage points, among workers without children the gender differences in pay disappear in such a scenario. Overall, these results suggest that policies aimed at closing the gender gap, either by correcting beliefs or by equalizing opportunities, mainly affect women without children, and therefore may have the unintended consequence of making the motherhood penalty larger.

Related literature This paper primarily relates to a large literature on the gender disparities in the labor market (Olivetti and Petrongolo, 2016; Blau and Kahn, 2017). Most of the earlier work focused on the role of human capital, discrimination, and occupational choices (Altonji and Blank, 1999). However, the sizable portion of the gender pay gap not accounted for by differences in measured qualifications and attributes has led researchers to search for answers by analyzing differences in behavioral traits (Bertrand, 2011; Flinn et al., 2020) as well as parenthood (Chung et al., 2017; Kleven et al., 2019; Andresen and Nix, 2019). We contribute to the literature by investigating a novel source of the gender gap in pay: male-female differences in labor market beliefs. First, we extend work by Reuben et al. (2017) and Bergerhoff et al. (2019), who document gender differences in wage expectations prior to entering the labor market. In particular, we show for a sample of experienced workers that women expect lower salaries but also a lower number of offers relative to their male counterparts, and that these differences explain a sizeable portion of the gender gap in reservation wages. Second, we quantify the importance of beliefs in accounting for the observed differences in labor market earnings between women and men.

Our results also speak to a growing literature that studies the role of information in the labor market. Recent papers (Caliendo et al., 2015; Conlon et al., 2018; Baley et al., 2020; Potter, 2021) have shown that imperfect information is an important feature of the job search process, affecting how workers are allocated to jobs and their earnings. Close to our work, Cortés et al. (2021) show through the lens of a job search model that the gender gap in accepted wages decreases by 20% when both females and males have perfect information about labor market earnings. Our paper complements theirs in two dimensions. First, we consider that individual's search behavior depends not only on their beliefs about the wage distribution, but also on their beliefs about the arrival rate, as in Spinnewijn (2015), and separation rate. In doing so, we show biased beliefs about arrival rates play a substantial role in the observed gender gap. Second, we bring to light important differences in the importance of beliefs due to motherhood. Specifically, we find that policies targeting beliefs as a way to close the gender gap change the search behavior of women without children but do not change the behavior of women with children. Hence, such policies may increase the earnings cost women suffer once they have children.

Overview The remainder of the paper proceeds as follows. In the next section, we describe the data and motivate the importance of labor market beliefs in the formation of reservation wages. In Section 3, we introduce individual heterogeneity in labor market beliefs and outcomes into a standard on-the-job search model. Section 4 describes the estimation procedure and Section 5 presents the counterfactual exercises.

2 Motivating Evidence

This section documents new evidence regarding gender differences in expectations about the labor market and how these play a role in explaining the reservation gender gap.

2.1 Data

We use an unbalanced panel from the Survey of Consumer Expectations (SCE) and its supplement Labor Market Survey (LMS). The sample period stretches from March 2015 to November 2019. The SCE surveys a representative sample of around 1,300 household heads across the US on a monthly basis. Each individual is surveyed every month for up to 12 months. In addition to this, every month for 4 months, the active members of the panel, those who participated in a monthly SCE in the prior three months, are eligible to participate in the LMS. Because each respondent is in the SCE panel for up to 12 months, he/she can participate in the LMS a maximum of three times during their tenure on the panel. The LMS elicits beliefs individuals hold about their prospects to receive a job offer in the future and their expectations about salary offers. Apart from elicited beliefs, the data provides information on many demographic variables as well as individuals' employment outcomes.

Sample As in Mueller et al. (2021), we restrict our focus to individuals with ages between 20 and 65. We further exclude individuals with missing information on key variables in the analysis[1] as well as those whose hourly wage or hourly expected wage is less than \$4/hr. The final dataset has 8031 observations from 4224 unique individuals. Table 1 shows the main characteristics of our analysis sample. Individuals are, on average, 42.5 years old, around 84% are white, and almost 43% have a college degree. Women make up slightly more than half of the sample. Male and female respondents differ in several dimensions, as shown in Columns 2 and 3 in Table 1 (column 3 of the table reports the p-value of the test of equality 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.

Labor Market Expectations and Outcomes We analyze expectations in two key dimensions of the labor market, the arrival rate, and the wage offer distribution. Let us briefly explain how these dimensions are captured in the survey. The LMS first asks all its respondents "*What do you think is the percent chance that within the coming four months, you will receive at least one job offer?*".[2] Conditional on reporting a non-zero likelihood of receiving at least one offer in the next four months, respondents are also asked about their expectations regarding the arrival of job offers and salary offers. In particular, 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.*" and "*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 the first question to measure individual beliefs about the arrival rate and the other two to measure expectations about the wage offer distribution. In addition to information about expectations, the survey elicits individual's willingness to accept future job offers by asking its respondents the following question: "*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?*". We use this question to measure the reservation wage. Along with data on expectations, the survey includes information on individual

[1] Specifically, we drop individuals with missing education, race, married/has partner, children, reservation wage or probability to receive job offer.

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

employment status and other standard labor market outcomes. Specifically, for individuals that reported having a job at the time of the survey, we observe annual earnings, job tenure, and industry. For those that are out of a job, we have information on unemployment duration and whether individuals are currently searching for a job or not. We also observe the number of offers received in the past 4 months and offered wages, and hence, we can link perceptions to actual outcomes for the same individuals.

In the survey, information about labor market earnings, either expectations or realizations, is given at the annual level, not accounting for hours worked. To address this issue, we convert all annual earnings variables into hourly earnings following the strategy employed by Conlon et al. (2018). First, we assume that individuals with a full-time job work 40 hours a week for 52 weeks a year, and those with a part-time job work 20 hours a week for 52 weeks a year. We then consider that the reservation wage and expected wages are about part-time work for those currently working in a part-time job and about full-time work for those currently working full-time. For those without a job, we assume that beliefs about earnings correspond to a full-time job. In addition to this, all earnings variables, realizations, and expectations are measured in July 2017 dollars using the consumer price index from the Bureau of Labor Statistics.

Table 2 reports summary statistics on labor market expectations and outcomes, showing differences between men and women in several dimensions. The average number of expected job offers ranges between 0.75 to 0.9, reflecting the fact that most workers do not expect to receive any job offer at all (across the four sub-samples the median is 0). On average, non-employed women expect to receive more offers than men. Regarding earnings, all women expect to be offered lower wages than men. The raw gender gap in the average expected wage is around \$7.1/hour among non-employed individuals and \$11.8/h among employed individuals. Gender differences in expectations about the best wage offer are of a similar magnitude.

Figure 1 compares individuals' beliefs with actual outcomes, i.e. offered wages and the number of offers received in the past four months. Panel A plots the distributions of wage expectations and the corresponding realizations separately by gender. One can observe that for both women and men, the distribution of the expected wage offer is to the right of the distribution of the actual wage offered. This suggests that both genders have wage expectations that tend to be higher than actual realizations. Nonetheless, the rightward shift is more pronounced for men: 75% of men believe they will be offered a higher wage than they are actually offered vs. 69% of women. The gap between expectations and realizations is larger for men, with men expecting, on average, to receive offers that pay more than 6\$/h than the actual offer, on average, while for females this gap is around 4.8\$/h. In addition to this, Panel B suggests that both genders tend to believe that they will receive more job offers than what they actually receive. Nonetheless, gender differences are small: the percentage of individuals positively biased is around 37% for both genders. Overall, the evidence we present here strongly suggests that individuals' beliefs about offered wages — in particular, those of men — are systematically biased upward as well as individuals' beliefs about job offers, as documented by Spinnewijn (2015) and Mueller et al. (2021). The documented gap between expectations and realizations can be interpreted either as a psychological attribute such as overconfidence or misinformation about labor market earnings and arrival rates.

Apart from gender differences in beliefs, Table 2 shows that, relative to men, women are also willing to accept lower hourly wages, with the gap amounting to \$8.1/hour and \$13.8/hour among the unemployed and the employed, respectively. Note that, both for females and males, the reservation wage is larger than the wage in the current job. This is consistent with the idea that currently employed workers ask for a larger wage than their current one to justify paying the cost of transitioning to a new job. With respect to search behavior, females are more likely to be looking for a job, regardless of employment status, but if employed receive slightly fewer offers than men. Finally, as expected, there is a substantial raw gap in labor market earnings, with women earning \$13.5/h less than men.

Other Variables Along with standard individual characteristics such as education, marital status, and parenthood, we use information from the survey on risk preferences. Specifically, we leverage two questions that aim to capture risk tolerance regarding financial matters and daily activities: *(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 both genders. For both tolerance to risk in financial matters and tolerance to risk in daily activities, 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 -0.44. 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).

2.2 Gender Differences in Labor Market Beliefs

While the raw data provide suggestive evidence of gender differences in expectations about labor market outcomes, such as offers and wages, we now take a step further and account for individual heterogeneity. Following the literature, we define the gender gap as the coefficient β_1 in the following regression,

$$y_{i,t} = \beta_0 + \beta_1 \, female_i + \gamma' x_{i,t} + \delta_s + \delta_t + \varepsilon_{i,t}. \tag{1}$$

Table 1: Descriptive Statistics: Sample

Variable (mean)	Full	Men	Women	p-value
Age	45.4	44.4	46.3	0.000
White	83.9	81.1	86.5	0.000
Black	8.8	12.4	5.5	0.000
Hispanic	9.9	9.6	8.2	0.037
College Degree or More	42.5	37.0	47.6	0.000
Children	33.2	35.7	34.0	0.146
Married/Has partner	66.8	72.5	60.5	0.000
# respondents	4224	2044	2180	
# observations	8031	3802	4229	

Notes: The table presents descriptive statistics for all respondents in the sample and also separately by gender. 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.

Table 2: Descriptive Statistics: Labor Market Beliefs & Outcomes

	Non-employed			Employed		
Variable (mean)	Men	Women	p-value	Men	Women	p-value
Panel A: Beliefs						
Likelihood receiving an offer (%)	19.6	25.0	0.001	25.6	24.3	0.101
Expected # job offers	.75	.91	0.006	.78	.8	0.119
Expected wage offered (average)	23.6	16.3	0.000	40.8	29	0.000
Expected wage offered (best)	29.2	20.2	0.000	46.8	33.3	0.000
Reservation Wage	31.7	22.5	0.000	46.2	32.4	0.000
Panel B: Outcomes						
Looking for a job (%)	19.9	24.9	0.012	21.0	25.3	0.000
Offers received	.19	.23	0.116	.39	.37	0.607
Offered wage	29.5	19.7	0.001	37.3	26.7	0.000
Wage	–	–	–	42.0	28.5	0.000
Duration (months)	44.1	57.5	0.000	95.0	78.0	0.000

Notes: The table reports means for each sub-sample of respondents. *Duration (months)* corresponds to the duration of the employment spell for employed individuals and to the unemployment duration for unemployed individuals, both measured in months. Labor market earnings — expectations and realizations — correspond to hourly amounts in dollars. 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.

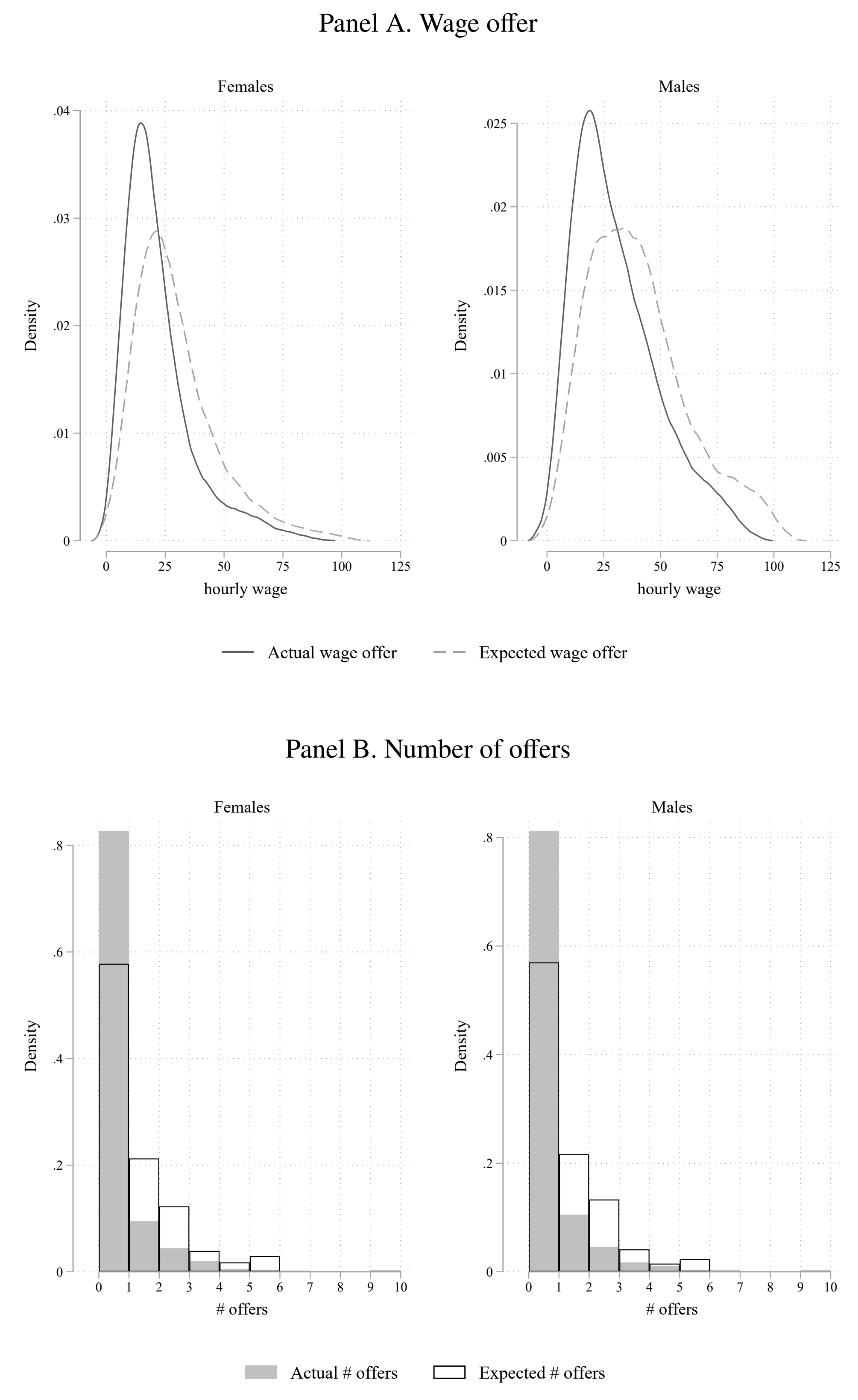

Figure 1: Expectations vs. Realizations

Notes: Panel A plots kernel densities of expected and actual wage offers per hour for females (left) and males (right). Panel B plots the distribution of the number of jobs individuals expect to receive in the following 4 months and the actual number of offers received in the last four months for both females (left) and males (right). 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.

where $female_i$ is a dummy equal to 1 if the respondent is female, $x_{i,t}$ is a vector of individual-level characteristics including age and its square, a measure of ability, dummy variables for education, race, whether she/he is married/lives with a partner or not. We also control for whether an individual is searching for a job or not and for unemployment or employment duration. The latter allows us to control for potential learning that occurs over the job search period, as suggested by Figure A.2.[3] Finally, δ_t are survey date fixed effects and $\varepsilon_{i,t}$ is the error term, which includes all unobserved determinants of outcomes for respondent i at time t. We estimateEquation 1 separately on a sample of non-unemployed and employed workers. The regression for employed workers also includes industry-fixed effects as a control. Panel A and B of Table 3 report, respectively, OLS estimates of β_1 in Equation 1 for the samples of non-employed and employed individuals.

Expectations gender gap We start by documenting differences between men and women in their beliefs about labor market outcomes. The first empirical regularity we highlight is a gender difference in the number of offers workers expect to receive in the next 4 months, but only among those that currently have a job. Column 1 in Panel A of Table 3 shows that among non-employed workers there is no statistical difference by gender, which stands in contrast to what one observes among employed workers, as shown in Panel B of Table 3). Specifically, we find that among those currently working there is a gender gap in expectations about the number of offers they will receive, with the coefficient on the female dummy being negative and significant at the 5% level.

The second empirical regularity we observe in Table 3 is that, when compared to their male counterparts, both employed and non-employed women have lower expectations about offered wages. This pattern holds regardless of whether we look to the average hourly wage across offers workers expect to receive or to the best expected offer in the next four months. As observed in Panel A of Table 3, columns 2 and 3, non-employed women's expectations about the average and best wage offer are 21.3% and 9.7% lower than that of men, respectively. In turn, among workers currently working, we observe a gender gap in the average and best expected offer of 6.2% and 5.7%, respectively. These differences are significant at the 1% level. Importantly, these estimates are cleansed from the effect of the current wage earned by employed workers (Panel B) or the wage earned in the last job by non-employed workers (Panel A).

Reservation wage gap Whether the above-described gender differences in expectations about the arrival rate and the wage offer distribution translate into actual wage gender differences, remains an open question. A potential explanation behind a strong link between expected and realized

[3]Figure A.2 presents a binned scatterplot of the relationship between expectation and the duration of the employment/unemployment duration for both genders. Both panels suggest that both man and females, whether employed or non-employed, revise their beliefs downwards about the number of job offers during unemployment and while on a job. Regarding expected wage offered, unemployed workers, both females, and males, seem to revise downwards their expectations as the unemployment duration increases. In contrast, expectations of employed males are constant across job tenure while females seem to revise their beliefs upward.

wages lies in individuals' willingness to accept a job offer. To shed light on this issue, we estimate a version of Equation 1 using the elicited reservation wages as an outcome variable. We proceed in three steps. First, we estimate the gender reservation wage gap adjusted for individual-level characteristics, as before, and job or previous job characteristics. Specifically, we control for the current wage if workers are employed or the wage of the previous wage if workers are not working at the time of the survey. Then, we estimate how much of the reservation wage gap can be explained by gender differences in risk preferences. Finally, we estimate the effect of the asked salary on the bid gap.

Consistent with earlier literature (Krueger and Mueller, 2016; Barbanchon et al., 2020), estimates of the gender dummy, reported in Panels A and B of Table 3 Column 4 indicate that, regardless of the employment status, women are willing to accept lower hourly wages than men. In particular, we estimate a reservation wage gap between men and women of 13.9% among non-employed workers and 4.1% among employed workers. The documented reservation wage gap is statistically significant at the 5% level. Following recent evidence by Cortés et al. (2021) showing that, among students who are looking for a first job after graduating from college, gender differences in reservation wages are driven by male-female differences in risk aversion, column 5 adds a measure of risk preference. Specifically, we include the simple average of the responses of both measures of risk preferences described previously in our regression. First, we note that the coefficient on risk tolerance is positive in line with Cortés et al. (2021)'s theoretical framework, which predicts that higher levels of risk aversion lead to lower reservation wages. Regarding gender differences in the reservation wage gap, once we control for risk preferences, the coefficient on the female dummy decreases slightly from 13.9% to 13.3% among non-employed workers, and from 4.1% to 3.7% among employed workers. This implies that gender differences in risk preferences, as measured in the SCE, explain, approximately 4% of the residual wage gap in reservation wages among non-employed individuals and 10% of the gap among employed individuals, respectively. Thus, in contrast to what Cortés et al. (2021) document among recent college graduate students, risk preferences do drive gender differences in the reservation wage among workers that have experience in the labor market.[4]

We then assess whether the documented gender gap in expectations can explain gender differences in the willingness to accept future job offers. To do so, we first add to our regression expectations about the best offer and then expectations about the number of job offers.[5] In doing so, we find that for non-employed workers, the gender gap in the reservation wage narrows to 8.6%. In other words, differences in expectations account for one-third of the gender reservation gap for non-employed individuals. For employed workers, controlling for the expectations about

[4]The results are similar if instead of the simple average of the risk preference measures we include both measures separately.

[5]Adding the average of the expected offered wage in the next 4 months, instead of the best expected offer, yields similar results.

the offered wage eliminates the gender reservation gap: the coefficient on the female dummy is no longer significant and its magnitude is very small (0.4%).

Overall, our results show that women have lower expectations about the offered wage, and this expectations gap explain a substantial part of the gender gap in the reservation wage. Taken together, these findings point toward the importance of expectations in the job search process and to its potential role in the determination of the gender gap in labor market outcomes through reservation wages. Therefore, in the next section, we incorporate individual-level heterogeneity in beliefs in an otherwise standard model of the labor market with on-the-job search. We then use the model as a laboratory to quantify the role of beliefs in shaping the gender wage gap.

3 Model

Time is continuous. There is a continuum of risk-neutral workers that share the same discount rate r.[6] Workers are heterogeneous with respect to a set of observable characteristics 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 the model parameters.

Labor Market Workers search on and off the job for jobs and randomly meet offers posted by firms in the labor market. 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 receive wage w, search on the job and receive job offers at the rate $\lambda_e(x_i)$. Both rates are assumed to be exogenous. Wage offers are drawn from the distribution $G(w|x_i)$. The wage offer distribution is exogenous and independent of the employment state. Finally, worker-firm pairs are destroyed at an exogenous rate $\delta(x_i)$.

Beliefs We assume that workers make decisions with possibly limited knowledge about future wage offers, contact rates, and exit rates. Thus, the true wage distribution, offer arrival rate, and separation rate are not known to the workers. Instead, workers have beliefs over the arrival and separation rates and wage offer distribution. We do not explicitly model the formation of these beliefs. In our setting, a worker with characteristics x_i believes the arrival rate of job offers while unemployed to be $\lambda_u^B(x_i)$ and while employed to be $\lambda_e^B(x_i)$. She also believes to be drawing wages from a distribution with cdf $G^B(w|x_i)$. Employed workers also have beliefs about the job separation rate $\delta^B(x_i)$.

[6]The assumption of risk neutrality follows from the results in n Section 2 showing that risk tolerance plays little role in explaining gender differences in the reservation wage.

Table 3: Gender Differences in Labor Market Beliefs

	exp. # offers	exp. wage (best)	exp. wage (ave.)	reservation wage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Non-employed							
female	-0.103	-0.097*	-0.213***	-0.139**	-0.133**	-0.086**	-0.086**
	(0.084)	(0.053)	(0.070)	(0.054)	(0.056)	(0.038)	(0.038)
risk tolerance					0.012	0.017	0.018
					(0.019)	(0.014)	(0.014)
exp. best offer						0.608***	0.607***
						(0.040)	(0.040)
exp. # offers							-0.004
							(0.014)
Observations	1537	944	944	820	820	820	820
Panel B: Employed							
female	-0.079**	-0.057***	-0.062***	-0.041**	-0.037**	-0.004	-0.004
	(0.040)	(0.016)	(0.023)	(0.017)	(0.017)	(0.012)	(0.012)
risk tolerance					0.011*	0.007	0.007
					(0.006)	(0.005)	(0.005)
exp. best offer						0.582***	0.582***
						(0.029)	(0.029)
exp. # offers							-0.001
							(0.006)
Observations	5484	4332	4332	3774	3774	3774	3774

Notes: The table reports coefficients from an OLS regression with robust standard errors clustered at the individual level. All columns 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 and survey date fixed effects. Panel B also includes industry-fixed effects. Columns 2 to 7 also control for the wage in the previous job (Panel A) and current wage (Panel B). *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.

Flow values The believed value of unemployment is given by:

$$rU^B(x_i) = b(x_i) + \lambda_u^B(x_i) \int_{R(x_i)}^{\bar{w}} E^B(w, x_i) - U^B(x_i)\, dG^B(w|x_i) \tag{2}$$

and the believed value of employment at a job with wage w is given by:

$$rE^B(w, x_i) = w + \lambda^B(x_i) \int_{w}^{\bar{w}} E^B(w', x_i) - E^B(w, x_i)\, dG^B(w|x_i) + \delta^B(x_i)[U^B(x_i) - E^B(w, x_i)]. \tag{3}$$

Reservation wage 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 in unemployment. For worker x_i, the reservation wage is therefore given by:

$$R(x_i) = b(x_i) + [\lambda_u^B(x_i) - \lambda_e^B(x_i)] \int_{R(x_i)}^{\bar{w}} \frac{1 - G^B(w|x_i)}{r + \delta^B(x_i) + \lambda_e^B(x_i)[1 - G^B(w|x_i)]}\, dw. \tag{4}$$

Steady State We solve for a steady state in which the unemployment rate, $u(x_i)$, for each worker type x_i does not change. The steady-state unemployment rate for worker x_i is

$$u(x_i) = \frac{\delta(x_i)}{\delta(x_i) + \lambda_u(x_i)[1 - G(R(x_i)|x_i)]}. \tag{5}$$

In steady state, the observed wage distribution $F(w|x_i)$ for each type of worker does not change $\frac{\partial F(w|x_i)}{\partial t} = 0$, hence, for worker type x_i, the mean of the observed wage distribution is given by:

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

See Appendix B for details.[7]

Equation 6 shows that differences in the average wage across worker types stem from differences in how fast workers climb the job ladder (the on-the-job finding rate, $\lambda_e(x_i)$), how fast they fall from the ladder (the separation rate, $\delta(x_i)$), the true underlying wage offer distribution $G(w|x_i)$ and from differences in individuals' willingness to accept a job $R(x_i)$. From Equation 4, we see that workers' beliefs affect the observed average wage only through the reservation wage.[8] To investigate the impact beliefs on wages, in Section 5, we use Equation 4 and Equation 6 to create counterfactual

[7]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.

[8]Alternatively, one could assume that expectations affect job search effort, and in this way the true job finding rates ($\lambda_e(x_i)$ and $\lambda_u(x_i)$), hence average wages (Equation 6). Using the Job Search Supplement from the SCE, Table A.1 shows that the number of applications sent in the last 4 weeks does not correlate with past expectations about number of offers and wage offers. Thus, our findings suggest that expectations may affect average wages through reservation wages rather than through true parameters.

reservation wages and average wages, for both men and women, in which we either change the beliefs or true parameter values.

4 Model Estimation

In this section, we estimate the model using the worker-level panel used in Section 2. We apply the same sample selection criteria. The underlying model parameters that we estimate are the believed and true job arrival rates of the unemployed and employed, the believed and true wage offer distributions and the believed and true separation rates; all parameters are estimated separately for men and women. Throughout, the vector of individual characteristics x_i includes a quadratic in age, an indicator for if the worker is married, an indicator for having a child, educational attainment, race, an indicator for high ability, and an indicator if the individual reported to be actively searching for a job. In what follows, we describe the strategy to pin down each model parameter.

4.1 Structural Assumptions

Job arrival rates In the model, each worker type x_i has a specific set of job arrival rates $\Omega(x_i) = \{\lambda_u(x_i), \lambda_e(x_i), \lambda_u^B(x_i), \lambda_e^B(x_i)\}$, where the superscript B stands for the believed parameters. We assume that the number of believed and true arrival offers for unemployed ($l = u$) and employed ($l = e$) workers follows a Poisson distribution with believed arrival rate $\lambda_l^B(x_i)$ and true arrival rate $\lambda_l(x_i)$, respectively. We assume that the true and believe arrival rates depend on the vector of observable characteristics x_i and an unobservable error term such that the *believed* arrival rate of job offers is given by:

$$\lambda_l^B(x_i) = \nu_{l,i}^B \cdot \exp(\beta_{l,1}^B \cdot x_i), \tag{7}$$

where $\nu_{l,i}^B \sim Gamma\big(k_{\nu_l}^B, \theta_{\nu_l}^B\big)$, and the *true* arrival rate of job offers is given by:

$$\lambda_l(x_i) = \nu_{l,i} \cdot \exp(\beta_{l,1} \cdot x_i) \tag{8}$$

where $\nu_{l,i} \sim Gamma\big(k_{\nu_l}, \theta_{\nu_l}\big)$. This implies that, conditional on observable characteristics x_i, both the believed and true arrival rate follow a Gamma distribution: $\lambda_l^B|x_i \sim Gamma\big(k_{\nu_l}^B, \theta_{\nu_l}^B \cdot \exp(\beta_{l,1}^B \cdot x_i)\big)$ and $\lambda_l|x_i \sim Gamma\big(k_{\nu_l}, \theta_{\nu_l} \cdot \exp(\beta_{l,1} \cdot x_i)\big)$, respectively; and, thereby, both the number of expected offers and the number of received offers follow a negative binomial distribution.[9]

Wage offer distributions We assume that the believed offered wage distribution follows a log-normal distribution with a mean that depends linearly on observable characteristics and an

[9] See Appendix C.1 for a derivation of the distributions.

unobservable error term ε_i^B that does not vary by employment status such that,

$$\ln w_i^B = c_2^B + \beta_2^B \cdot x_i + \varepsilon_i^B \tag{9}$$

where $\varepsilon_i^B \sim N(0, \sigma^B)$. Therefore, the believed wage offer follows a log-normal distribution with CDF G_i^B, that is, $w_i^B | x \sim G^B(w_i; \mu_i^B, \sigma^B)$, where $\mu_i^B = c_2^B + \beta_2^B \cdot x_i$. Regarding the true offered wage distribution, we also assume that the log wage depends linearly on the set of observable characteristics x_i and an error term $\varepsilon_i \sim N(0, \sigma)$ such that

$$\ln w_i = c_2 + \beta_2 \cdot x_i + \varepsilon_i. \tag{10}$$

Therefore, the true wage offer distribution also follows a log normal distribution with cdf $G_i \sim \ln N(\mu_i, \sigma)$ where $\mu_i = c_2 + \beta_2 \cdot x_i$.

Separation rates In the model, a worker with characteristics x_i believes separations occur at a Poisson rate $\delta^B(x_i)$, and true separations occur at a Poisson rate $\delta(x_i)$. We assume that the separation rate of jobs, both the believed and the true one, depends on the observable characteristics x_i and an error term. As such, the believed arrival rate of job separation is given by:

$$\delta^B(x_i) = \phi_i^B \cdot \exp(\beta_3^B \cdot x_i), \tag{11}$$

where the error term $\phi_i^B \sim Gamma(k_\phi^B, \theta_\phi^B)$, and the true arrival rate of separation is given by:

$$\delta_i(x_i) = \phi_i \cdot \exp(\beta_3 \cdot x_i), \tag{12}$$

where the error term $\phi_i \sim Gamma(k_\phi, \theta_\phi)$.

4.2 Likelihood Function

We estimate the model parameters using maximum likelihood. We leverage a set of questions from the LMS and individual outcomes to discipline the parameters of the model. For both employed and unemployed workers, we use the following survey questions to inform us about the true job arrival rates and wage offer distribution, respectively: *(i) How many job offers did you receive in the last 4 months? Remember a job offer is not necessarily a job that you accepted.*, and *(ii) What was the annual salary of this job offer? And was it for a full-time or a part-time job? / Thinking about the 3 best job offers that you received in the last 4 months, What was their annual salary? And were they for a full-time or a part-time job?* We also gain information about these parameters from the observed wage distribution of employed workers.

As explained in Section 2, the LMS starts by asking its respondents about the likelihood that they will receive at least one job offer in the coming four months, and, conditional on reporting a non-zero likelihood, the respondents are then asked about their expectations about the number of offers in the next four months and the annual salary of the best offer. We use the responses to these three questions to pin down the values for the believed arrival rate of job offers and the believed wage offer distributions. Regarding the separation rates, for employed workers, we gain information about the parameters that govern the believed separation rate through the following survey question: *What do you think is the percent chance that four months from now you will be...[unemployed]?*; and we use the observed unemployment probability across the population and the observed employment duration to inform the separation rate;

Finally, to construct the likelihood function we assume that all error terms are independent, $\nu^B_{l,i} \perp \nu_{l,i} \perp \varepsilon_i \perp \varepsilon^B_i \perp \phi^B_i \perp \phi_i$ for both $l \in \{u, e\}$, that is, we assume that the errors in reported arrivals, wages and separations are independent conditional on all observable characteristics. In what follows, we described the contribution of an unemployed worker and an employed worker to the likelihood function in terms of the probability of observing the given information. All functional forms of these probabilities are detailed in Appendix C.1.

Unemployed Worker's Contribution Let $p_{u,i}$ be the probability that an unemployed individual believes to receive at least one offer, $n^B_{u,i}$ be the number of offers they expect to receive, and $\bar{w}^B_i$ be the best wage they expect to be offered, $n_{u,i}$ be the number of offers the worker actually received and $w_{i,1} \geq w_{i,2} \geq w_{i,3}$ be the best three offers received. The probability of observing an individual with $p_{u,i}$, $n^B_{u,i}$, $\bar{w}^B_i$, $n_{u,i}$ and the set $\tilde{w}_i = \{w_{i,1}, w_{i,2}, w_{i,3}\}$ conditional on observables x_i and being unemployed is given by

$$\begin{aligned} P(p_{u,i}, n^B_{u,i}, \bar{w}^B_{u,i}, n_{u,i}, \tilde{w}_i | x_i, u_i) = & [P(p_{u,i} > 0 | x_i, u_i) P(n^B_{u,i} | p_{u,i}, x_i, u_i) P(\bar{w}^B_{u,i} | p_{u,i}, n^B_{u,i}, x_i, u_i)]^{\mathbb{1}(p_{u,i}>0)} \\ & \times P(p_{u,i} = 0 | x_i, u_i)^{\mathbb{1}(p_{u,i}=0)} \times P(n_{u,i} = 0 | x_i, u_i)^{\mathbb{1}(n_{u,i}=0)} \\ & \times [P(w_{i,1} | n_{u,i} = 1, x_i, u_i) P(n_{u,i} = 1 | x_i, u_i)]^{\mathbb{1}(n_{u,i}=1)} \\ & \times [P(w_{i,1}, w_{i,2} | n_{u,i} = 2, x_i, u_i) P(n_{u,i} = 2 | x_i, u_i)]^{\mathbb{1}(n_{u,i}=2)} \\ & \times [P(w_{i,1}, w_{i,2}, w_{i,3} | n_{u,i} \geq 3, x_i, u_i) P(n_{u,i} \geq 3 | x_i, u_i)]^{\mathbb{1}(n_{u,i}\geq 3)}, \end{aligned} \tag{13}$$

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

Employed Worker's Contribution Similarly for employed workers, let $p_{e,i}$ be the probability that an employed individual believes to receive at least one offer, $n^B_{e,i}$ be the number of offers they expect to receive, $\bar{w}^B_i$ be the best wage they expect to receive, $n_{e,i}$ be the true number of offers the workers actually received and let $w_{i,1} \geq w_{i,2} \geq w_{i,3}$ be the best three offers received. Let d_i be the observed employment duration of worker i, let w_i^c be the current wage of the worker, and let s_i^B be the worker's believed 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 observables and being unemployed is given by

$$\begin{aligned}
P(p_{e,i}, n_{e,i}^B, \bar{w}_{e,i}^B, n_{e,i}, \tilde{w}_i, d_i, w_i^c | x_i, e_i) = \\
& [P(p_{e,i} > 0 | x_i, e_i) P(n_{e,i}^B | p_{e,i}, x_i, e_i) P(\bar{w}_{e,i}^B | p_{e,i}, n_{e,i}^B, x_i, e_i)]^{\mathbb{1}(p_{e,i}>0)} \\
& \times P(p_{e,i} = 0 | x_i, e_i)^{\mathbb{1}(p_{e,i}=0)} \times P(n_{e,i} = 0 | x_i, e_i)^{\mathbb{1}(n_{e,i}=0)} \\
& \times [P(w_{i,1} | n_{e,i} = 1, x_i, e_i) P(n_{e,i} = 1 | x_i, e_i)]^{\mathbb{1}(n_{e,i}=1)} \\
& \times [P(w_{i,1}, w_{i,2} | n_{e,i} = 2, x_i, e_i) P(n_{e,i} = 2 | x_i, e_i)]^{\mathbb{1}(n_{e,i}=2)} \\
& \times [P(w_{i,1}, w_{i,2}, w_{i,3} | n_{e,i} \geq 3, x_i, e_i) P(n_{e,i} \geq 3 | x_i, e_i)]^{\mathbb{1}(n_{e,i}\geq 3)} \\
& \times P(d_i | w_i^c, x_i, e_i) P(w_i^c | x_i, e_i) \times P(s_i^B | x_i, e_i) \qquad (14)
\end{aligned}$$

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

Complete Likelihood Function The overall log-likelihood function for the whole sample is given by:

$$\begin{aligned}
\ln \mathcal{L} = \sum_{i=1}^{N} & \mathbb{1}(u_i = 1) \times [\ln P(p_{u,i}, n_{u,i}^B, \bar{w}_{u,i}^B, n_{u,i}, \tilde{w}_i | x_i, u_i) + \ln P(u_i | x_i)] \\
& + \mathbb{1}(u_i = 0) \times [\ln P(p_{e,i}, n_{e,i}^B, \bar{w}_{e,i}^B, n_{e,i}, \tilde{w}_i, d_i, w_i^c | x_i, e_i) + \ln P(e_i | x_i)] \qquad (15)
\end{aligned}$$

where u_i is an indicator variable that takes on the value 1 if the worker is unemployed and 0 otherwise, and $e_i = 1 - u_i$.

Estimation By maximizing Equation 15, we obtain estimates of the effect of individual heterogeneity x_i on the believed and true job arrival rates, the believed and true wage offer distributions, and the believed and true job separation rates, as well as the parameters of the error terms for the, believed and true job arrival rate, the believed and true wage, and the believed and true job separation rates. All parameters are estimated separately for men and women, and therefore are gender-specific. For the estimation, we residualized the believed wage offers, the true wage offers, and the reservation wage from the effects of commuting zone, industry and its interaction with education, and employment/unemployment duration. Table C.1 in Appendix C.2 reports the estimate parameter values for the job arrival rates and Table C.2 reports the estimated parameter values for the wage offer distributions. The parameters that govern job separation are reported in Table C.3.

4.3 Flow value of Unemployment

We compute the flow value of unemployment for each worker i as the residual between the individual's reported reservation wage and the reservation wage predicted by the model predicted. Specifically, for each respondent, we observe the reported reservation wage, $R(x_i)$, the believed job arrival rates $\hat{\lambda}_u^B(x_i) = \mathbb{E}[\lambda_u^B|x_i]$ and $\hat{\lambda}_e^B(x_i) = \mathbb{E}[\lambda_e^B|x_i]$, the believed wage offer distribution $\hat{G}_i^B \sim \ln N(\hat{\beta}_2 \cdot x_i, \hat{\sigma}^B)$, and the believed separation rate $\hat{\delta}^B(x_i) = \mathbb{E}[\delta^B|x_i]$. Using Equation 4, the estimated flow value of unemployment is given by

$$\hat{b}(x_i) = R(x_i) - \left[\hat{\lambda}_u^B(x_i) - \hat{\lambda}_e^B(x_i)\right] \int_{R(x_i)}^{\bar{w}} \frac{1 - \hat{G}^B(w|x_i)}{r + \hat{\delta}^B(x_i) + \hat{\lambda}_e^B(x_i)[1 - \hat{G}^B(w|x_i)]} \, dw. \tag{16}$$

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

$$\hat{b}(x_i) = c_4 + \beta_4 \cdot x_i + \xi_i \tag{17}$$

and estimate β_4 using OLS. Table C.4 in Appendix C.2 reports the estimate parameter values for the flow value of unemployment.

4.4 Model Fit

Table 4 shows that the model provides a very good fit for the data, reproducing essential features of the labor market. The model closely matches the reservation wages of men and women, regardless of the employment status, as well as the average wages. Given the average wages of women and men predicted by the model, the gender gap in pay, defined as the difference in women's and men's earnings as a percentage of men's earnings, is 0.31%, which compares to 0.34% in the data. Similarly, the proportion of unemployed men and women in the data and predicted by the model are nearly identical. The model somewhat understates employment duration for women in about 7.7 months (9.6%) and for men in about 17 months (17%).

Table 4: Model Fit

	Men		Women	
	Data	Model	Data	Model
Reservation Wage, Unemployed (Average)	8.41	8.41	5.76	5.78
Reservation Wage, Employed (Average)	8.74	8.77	6.02	6.32
Wage (Average)	14.30	14.08	9.39	9.73
Unemployment Rate	0.20	0.21	0.27	0.27
Employment Duration Women (Months)	99.58	82.53	79.64	71.95

Notes: The table compares model-based moments to data-based moments for both men and women.

5 Sources of Gender Differences in Wages

With the estimated parameters in hand, we use the model to understand the role played by beliefs and true labor market parameters in generating gender differences in wages and welfare. We consider three counterfactuals. First, we make women's beliefs about labor market parameters as biased as those of men. Second, we correct men's and women's labor market beliefs, making them unbiased. Third and finally, we shut down gender differences in true labor market parameters, i.e. we set women's underlying labor market parameters equal to those of men, while holding the bias in their beliefs fixed. It is important to note that all counterfactuals are partial equilibrium exercises as we assume that changing labor market beliefs does not changes true parameters.[10] Furthermore, all counterfactuals are calculated for the whole sample and take into consideration the probability of employment when the reservation wage changes. For each counterfactual, we report the reservation wage, average wage and welfare computed as follows.

Reservation Wage We compute the model predicted reservation wage for women and men of type x_i $\left(\tilde{R}(x_i)\right)$ using Equation 4 and the counterfactual parameters.

Average Wage Combining $\tilde{R}(x_i)$ with Equation 6, we predict the average wage for women and men of type x_i $\left(\tilde{\mathbb{E}}_i[w]\right)$. To construct the counterfactual average wage, we take a weighted average of all individuals in the data, each weighted by their employment probability, that is,

$$\tilde{\mathbb{E}}[w] = \sum_{i=1}^{N} \left(1 - \tilde{u}(x_i)\right) \cdot \tilde{\mathbb{E}}[w|x_i]. \tag{18}$$

where the probability of being unemployed $(\tilde{u}(x_i))$ is computed using the steady-state unemployment rate, Equation 5.

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. The assumption of risk neutrality leads to a simple formula for the consumption-equivalent variation. Denoting, for a given type i, the welfare for men W_i^M and W_i^F for women, the gender gap in welfare Λ is given by

$$\Lambda = \frac{\sum_i W_i^F/N}{\sum_i W_i^M/N} - 1 \tag{19}$$

where the numerator is the average welfare for men and the denominator the average welfare for women across the population. The welfare functions W_i^M and W_i^F are the discounted sum of

[10] Table A.1 shows that past expectations about the number of offers or the wage offered do not correlate with the number of applications sent, suggesting that having higher expectations is not associated with higher job search effort. We interpret this result as suggestive evidence that expectations do not affect true parameters such as the true job arrival rate.

consumption for men and women of type i defined as

$$W_i = \int_0^\infty b(x_i) \cdot u_t(x_i) + \mathbb{E}[w|x_i] \cdot \left(1 - u_t(x_i)\right) dt \tag{20}$$

$$\text{s.t.} \quad \dot{u}_t(x_i) = \delta(x_i) \cdot u_t(x_i) + \lambda_u(x_i) \cdot \left[1 - G(R(x_i)|x_i)\right] \cdot \left(1 - u_t(x_i)\right)$$

where each parameter is gender-specific and $\mathbb{E}[w|x_i]$ is given by Equation 6. For computational reasons we use the steady state observed wage distribution F but allow welfare to include the transition of the unemployment rate. We solve the change in unemployment with the initial condition that at time $t = 0$ everyone is unemployed. The resulting unemployment rate for a female or male worker of type i at time t is given by

$$\begin{aligned} u_t(x_i) = & \frac{\delta(x_i)}{\delta(x_i) + \lambda_u(x_i) \cdot \left[1 - G(R(x_i)|x_i)\right]} \\ & + \frac{\lambda_u(x_i) \cdot \left[1 - G(R(x_i)|x_i)\right]}{\delta(x_i) + \lambda_u(x_i) \cdot \left[1 - G(R(x_i)|x_i)\right]} \cdot \exp\left\{ -\left(\delta(x_i) + \lambda_u(x_i) \cdot \left[1 - G(R(x_i)|x_i)\right]\right)t \right\}. \end{aligned} \tag{21}$$

Bias in beliefs Before proceeding to the results of the counterfactual analysis, let us describe how we measure bias in beliefs about labor market parameters. We define *bias* as the percent difference between the estimated believed and true parameters, that is the difference between the estimated believed and true parameters of the model in logs. For a worker of type x_i and gender g, the bias in the parameter y is given by

$$bias_{y_g}(x_i) = \mathbb{E}[\ln \hat{y}^B_{i,g}] - \mathbb{E}[\ln \hat{y}_{i,g}]. \tag{22}$$

where $\hat{y}^B_{i,g}$ is the estimated believed parameter y and $\hat{y}_{i,g}$ is the estimated true parameter y. The details for the bias of each parameter are provided in Appendix D. Table 5 reports the average bias for each labor market parameter, showing that both men and women have upward biased beliefs about labor market parameters. Specifically, men believe the mean of the wage offer distribution is 0.57% higher than the true mean wage offer draw, while women believe the mean of the wage offer distribution to be about 0.54% higher than the true one. Regardless of the employment status, both men and women have upward biased beliefs about the arrival rate of job offers, albeit the extent of the bias is larger when individuals are unemployed. Finally, both men and women believe their chances of staying employed are better than what they actually are, that is, the bias on the separation rate is negative. The extent of the bias is slightly larger for women. These results are in line with the suggestive evidence from our dataset, as described Section 2 and with Bandiera et al. (2022), who show in a meta-study that both men and women tend to have upwardly biased beliefs.

Table 5: Average Bias in Labor Market Beliefs

	Men	Women
Mean Wage Offer	0.57	0.54
Standard Deviation Wage Offer	-0.14	-0.13
Unemployed Job Arrival Rate	17.73	16.93
Employed Job Arrival Rate	2.02	2.11
Separation Rate	-0.17	-0.80

Notes: The table reports the average bias in beliefs about labor market parameters for men and women as defined in Equation 22. We compute the bias for each individual type x_i and report the sample weighted average.

5.1 Equally Biased Beliefs

In the first counterfactual, we make women's beliefs about labor market parameters as biased as men's. To do so, we set women's bias in beliefs equal to that of men by computing new parameters for labor market beliefs, holding fixed the true parameters. This implies that, for women with characteristics x_i, the counterfactual believed parameter is equal to the true parameter for women plus the bias in the men's beliefs relative to that same parameter, that is,

$$\mathbb{E}[\ln \tilde{y}^B_{i,F}] = \mathbb{E}[\ln \hat{y}_{i,F}] + bias_{y_M}(x_i). \tag{23}$$

where $\hat{y}_{i,F}$ is the estimated true parameter for women and $bias_{y_M}(x_i)$ is the bias in men's belief about parameter y, where y is the arrival rates, the mean and variance of the offer wage distribution, and the separation rate.

Table 6 describes the baseline model (row 1) and results from counterfactuals when women are as biased as men (rows 2-4). Removing gender differences in bias decreases the gender gap in reservation waged and average wage by 3 and 2.3 percentage points, respectively, while the welfare gap remains barely unchanged. The last 3 rows of Table 6 decompose the effect of biased beliefs by making women equally biased in arrival rates, separation rates, and wage offer distributions one at a time. Making women equally biased in the arrival rate of job offers decreases the reservation wage gap to 15% and decreases the wage gap to 24%, however, doing so increases the welfare gap by nearly 1 percentage point. The difference between the effects on average wages and welfare is driven by the length of time workers spend unemployed. The more biased workers' beliefs are, the further they are from making the welfare-maximizing decision to leave unemployment at the correct time. If workers' beliefs about their job-finding rate while unemployed are upward biased, their reservation wages will be too high and thus workers will spend more time employed, decreasing their lifetime welfare. Alternatively, if the beliefs about job-finding rate while employed are upward biased, the reservation wage will be too low and workers will spend less time in unemployment than optimal, decreasing also their lifetime welfare. Since men's beliefs are more upward biased than women's beliefs, when making women as biased as men, this translates into higher wages (the average wage increases by 10%), but it also leaves them unemployed longer and moves them further away from their maximum lifetime welfare. As a consequence, the gender welfare gap increases. The last two rows of the table show that the bias in separation rates and the offer distribution do not play a large role in the gender gaps by themselves.

Table 6: Counterfactual: Equally Biased Beliefs

	Reservation Wage		Wage		Welfare	
	Women	Gap	Women	Gap	Women	Gap
Model	6.18	28.98	9.73	30.91	7.73	34.31
All Beliefs	6.44	26.01	10.06	28.57	7.73	34.26
Believed Arrival Rates	7.43	14.58	10.74	23.70	7.63	35.09
Believed Separation Rate	6.19	28.84	9.64	31.49	7.71	34.44
Believed Offer Distribution	6.23	28.42	9.74	30.78	7.73	34.30

Notes: The table reports the average reservation wage, wage, and welfare as well as the gender gap from the baseline model (row 1) and counterfactuals in which women's beliefs are as biased as men's beliefs (rows 2-5). The gender gap in the reservation wage and wage (columns 2 and 4) is defined as the difference in women's and men's outcomes expressed relative to men's outcome (i.e. $(w_f/w_m - 1) \cdot -100$). Welfare is reported as W/r. The welfare gap (column 6) is $\Lambda \cdot -100$, where Λ is given by Equation 19. In all counterfactuals, men's average reservation wage, wage, and welfare are fixed to their baseline values: 8.70, 14.70, and 11.76, respectively.

5.2 Unbiased Beliefs

In the second counterfactual exercise, we correct labor market beliefs, i.e. we set women's and men's beliefs to be unbiased. This implies that we compute the reservation wage as in Equation 4, but using the estimated true parameters rather than the estimated believed parameters.

Table 7 reports the baseline model (row 1) and the results from such counterfactual (rows 2-4). Eliminating bias in beliefs about all the labor market parameters widens the reservation wage gap from 31% to 38%. As a consequence, pay inequality between gender increases. This is because the increase in pay for women from \$9.7 to \$ 11.1 (an increase of 13%) is offset by a larger increase in pay for men, from \$8.7 to \$12.1 (an increase of 27%). The effect of making the arrival rate of job offers while employed unbiased overpowers the effects of the separation rate and offer distribution which decreases the reservation wages; this can be seen in the last two rows of the table. Having unbiased beliefs provides workers the maximum lifetime welfare, \$12.59 for men and \$7.83 for women. However, it also increases the welfare gap by 3.5 percentage points. The increase in the welfare gap is driven by the fact that women's beliefs are less upward biased when compare to those of men and therefore already closer to their maximized lifetime welfare.

The last row in Equation 4 shows the results when only the beliefs about the wage offer distribution are corrected. This mimics an information intervention such as the pay transparency policies, whereby firms are required to provide information on pay. Consistent with recent empirical evidence on the effect of such policies (Gulyas et al., 2021; Duchini et al., 2022; Bennedsen et al., 2022), we find that such an information shock about the wage offer distribution has small effects on the gender gap in pay, narrowing it down only in 1 percentage point. The magnitude of the gender gap decrease in the model is between the size of the effect found by Gulyas et al. (2021) and Bennedsen et al. (2022). The key mechanism that drives the reduction in the gender gap pay in the model is a 2.8% reduction in men's pay, which is larger than the reduction in women's pay. This is because men's beliefs about the wage offer distribution are further away from the true offer distribution. Our results are in line with the findings Bennedsen et al. (2022), who show that an information shock in Denmark led to a decrease in men's pay, reducing the gender pay gap. Overall, our results show that making workers' beliefs about the labor market unbiased does little to close the wage or welfare gap between men and women.

Table 7: Counterfactual: Unbiased Beliefs

	Reservation Wage			Wage			Welfare		
	Men	Women	Gap	Men	Women	Gap	Men	Women	Gap
Model	8.70	6.18	28.98	14.08	9.73	30.91	11.76	7.73	34.31
All Beliefs	12.13	7.49	38.22	17.91	11.08	38.14	12.59	7.83	37.82
Believed Arrival Rates	15.50	8.69	43.97	21.72	12.68	41.59	11.49	7.64	33.50
Believed Separation Rate	8.59	6.19	28.00	13.99	9.72	30.53	11.58	7.73	33.22
Believed Offer Distribution	8.33	6.13	26.40	13.68	9.59	29.94	11.58	7.70	33.44

Notes: The table reports the average reservation wage, wage, and welfare as well as the gender gap from the baseline model (row 1) and counterfactuals in which beliefs about labor market parameters are unbiased for both men and women (rows 2-5). The gender gap in the reservation wage and wage (columns 3 and 6) is defined as the difference in women's and men's outcomes expressed relative to men's outcome (i.e. $(w_f/w_m - 1) \cdot -100$). Welfare is reported as W/r. The welfare gap (column 9) is $\Lambda \cdot -100$, where Λ is given by Equation 19.

5.3 Equalizing True Parameters

We now investigate the role of true parameters in generating gender differences in the labor market. To do so, we set women's labor market parameters equal to those of men, while holding the bias in their beliefs fixed. This means that, for each parameter, we compute a counterfactual believed parameter as the men's true parameter plus the bias in women's beliefs with respect to that parameter:

$$\mathbb{E}[\ln \tilde{y}^B_{i,F}] = \mathbb{E}[\ln \hat{y}_{i,M}] + bias_{y_F}(x_i). \tag{24}$$

where $\hat{y}_{i,M}$ is the estimated true parameter for men and $bias_{y_F}(x_i)$ is the bias in women's belief about parameter y, where y is the job arrival rates, the mean and variance of the offer wage distribution, and the separation rate.

Table 8 reports the benchmark model (row 1) and the results of simulating such counterfactual. Removing gender differences in all labor market parameters (row 2), narrows down the gender gap in wages to 25% and gender differences in welfare from 34% to 19%. While in such a scenario women are willing to accept lower-wage offers (the reservation wage decreases by 28%), this is offset by the fact that now women draw wages from a distribution with a higher mean. As consequence, the average wage increases substantially, and inequality in pay across genders decreases. The last three rows of Table 8 report the effects of giving women the same true parameters while holding their bias in beliefs fixed separately for each of the parameters. We find that equalizing the true offer distribution has the largest effect on wages, increasing women's average wages to \$10.72 and decreasing the wage gap by 7 percentage points. The welfare gap also decreases by 7 percentage points when men and women face the same true offer distribution.

The three counterfactual exercises show that policies aimed at changing workers' beliefs can decrease the observed wage gap, specifically when making women as biased as men in terms of job arrival rates. However, this does not translate into a decrease in the welfare gap since women choose to spend more time in unemployment. Alternatively, making workers completely unbiased increases both the average wage gap and welfare gap. On the other hand, policies aimed at changing the true offer distribution of women can decrease the average wage gap and the welfare gap.

Table 8: Counterfactual: True Parameters

	Reservation Wage		Wage		Welfare	
	Women	Gap	Women	Gap	Women	Gap
Model	6.18	28.98	9.73	30.91	7.73	34.31
All Parameters	4.42	49.20	10.58	24.84	9.58	18.52
Arrival Rates	4.92	43.51	9.16	34.90	8.28	29.55
Separation Rate	6.20	28.78	9.82	30.24	7.83	33.46
Offer Distribution	6.16	29.22	10.72	23.83	8.60	26.88

Notes: The table reports the average reservation wage, wage and welfare as well as the gender gap from the baseline model (row 1) and counterfactuals where women's true labor market parameters are set equal to those of men (rows 2-5). The gender gap in the reservation wage and wage (columns 2 and 4) is defined as the difference in women's and men's outcome expressed relative to men's outcome (i.e. $(w_f/w_m - 1) \cdot -100$). Welfare is reported as W/r. The welfare gap (column 6) is $\Lambda \cdot -100$, where Λ is given by Equation 19. In all counterfactuals, men's average reservation wage, wage and welfare are fixed to their baseline values: 8.70, 14.70 and 11.76, respectively.

5.4 Heterogeneity in Parenthood

The counterfactual analysis thus far has focused on average reservation wages, wages, and welfare across all individuals in our sample. Following recent literature that finds evidence the gender pay gap widens significantly after the birth of the first child (Chung et al., 2017; Kleven et al., 2019), we now explore heterogeneity along the parenthood dimension. To do so, we recompute each counterfactual separately for individuals with and without children, assuming they are 35-year-old workers with a college degree, have high ability, and are searching for a job.

Panel A of Table 9 reports the results for men and women without children. Two results stand out. First, if women with no children were as biased as men with no children, the gender wage gap would decrease by 5 percentage points, and as before the welfare gap would remain unchanged (row 2 of Panel A). Second, equalizing women's true parameters to those of men eliminates entirely the gender wage gap and decreases the welfare gap by 10 percentage points. This contrasts with what happens among men and women with children, as shown in Panel B of Table 9. First, the model estimated gap in earnings and welfare is equal to 40% and 37%, respectively. This is substantially larger than the wage gap among non-parents. Second, making mothers' beliefs as biased as those of the fathers does not change the wage, unlike their childless counterparts (row 2 of Panel B). Finally, changing the true parameters for women can decrease the wage gap between parents by 8 percentage points and eliminate entirely the welfare gap (row 3 of Panel B).

The fact that beliefs affect mothers and non-mothers differently implies that policies that target beliefs can have the unintended consequence of making the motherhood penalty larger as these mainly affect the job search behavior of women without children. In the estimated model, women without children have an average wage of \$12.02 and mothers have an average wage of \$9.58, implying a motherhood penalty of 11%. A policy that intends to correct workers' beliefs would increase the average wage of women without children to \$12.78 and decrease the average wage for mothers to \$9.44, therefore increasing the motherhood penalty to 26%. Similarly, the motherhood penalty in welfare would increase from 19% to 21%. Therefore, making workers unbiased would make mothers worse off, not only compare to fathers but also compared to women without children. Alternatively, policies targeting the true parameters would increase the motherhood penalty in wages to 32% but the welfare of mothers would increase above that of women without children.

6 Conclusion

This paper sheds light on the importane of labor market beliefs in generating differences in pay between women and men. We first show that the reservation wage gap is driven by differences in expected labor market outcomes. We then incorporate individual-level heterogeneity in beliefs in an otherwise standard model of the labor market with on-the-job search to quantify the role of

Table 9: Counterfactuals: Heterogeneity by Parenthood

	Reservation Wage			Wage			Welfare		
	Men	Women	Gap	Men	Women	Gap	Men	Women	Gap
Panel A: Without Children									
Model	10.07	8.10	19.59	16.11	12.02	25.40	15.19	11.58	23.81
Equally Biased	10.07	11.50	-14.15	16.11	12.80	20.53	15.19	11.71	22.90
Unbiased	14.22	11.06	22.21	17.55	12.78	27.16	15.39	11.77	23.57
True Parameters	10.07	0.00	100.00	16.11	16.12	-0.06	15.19	13.07	13.96
Panel B: With Children									
Model	9.49	7.05	25.68	16.06	9.58	40.33	15.02	9.37	37.65
Equally Biased	9.49	6.20	34.69	16.06	9.62	40.07	15.02	9.43	37.26
Unbiased	14.26	7.96	44.21	18.38	9.44	48.64	15.41	9.25	40.00
True Parameters	9.49	11.79	-24.28	16.06	10.83	32.57	15.02	15.45	-2.83

Notes: The table reports the average reservation wage, wage, and welfare for men and women, and the percent difference between men and women for the three counterfactual exercises. *Equally Biased* corresponds to a counterfactual in which women's beliefs about all labor market parameters are as biased as those of men. *Unbiased beliefs* corresponds to the counterfactual in which we correct all beliefs about the labor market for both men and women. *True Parameters* sets women's true parameters equal to the men's parameters. In all counterfactuals, parameters are predicted for a 35-year-old married man and women with a college degree, high ability, and searching for a job.

beliefs in shaping the gender wage gap.

Using the estimated model, we find that beliefs are an important factor behind the gender gap in pay. However, eliminating differences in beliefs, either by making women as biased as men or by correcting beliefs, fails to close the gender gap in welfare. By contrast, equalizing opportunities in the labor market, that is, a scenario in which women would have the same offer distribution or job arrival rates as men, narrows down the gender gap in pay and welfare. 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

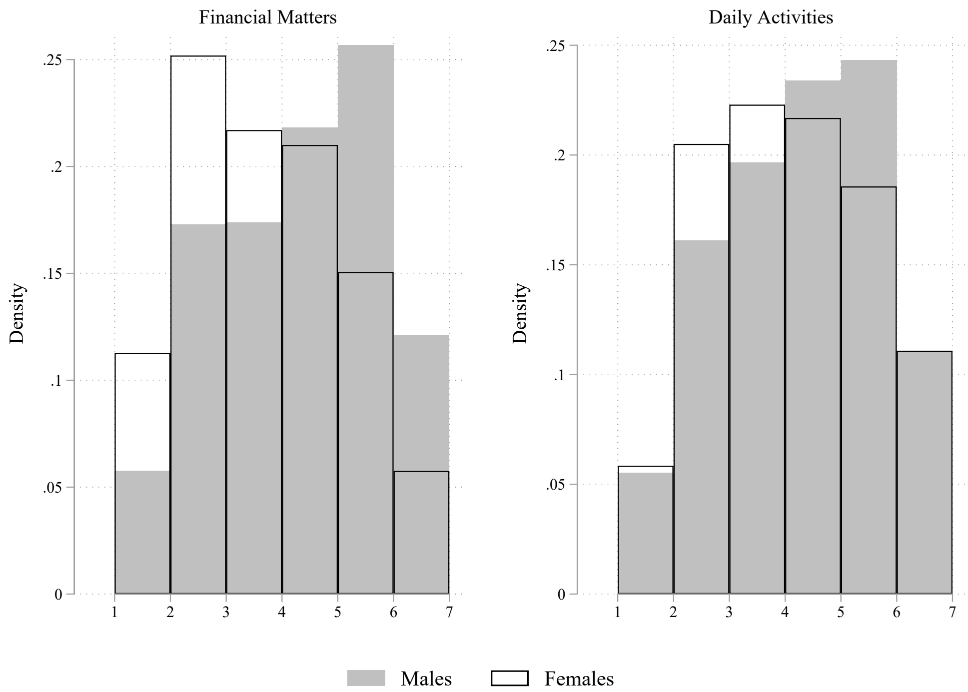

Figure A.1: Risk Tolerance: Females vs. Males

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.

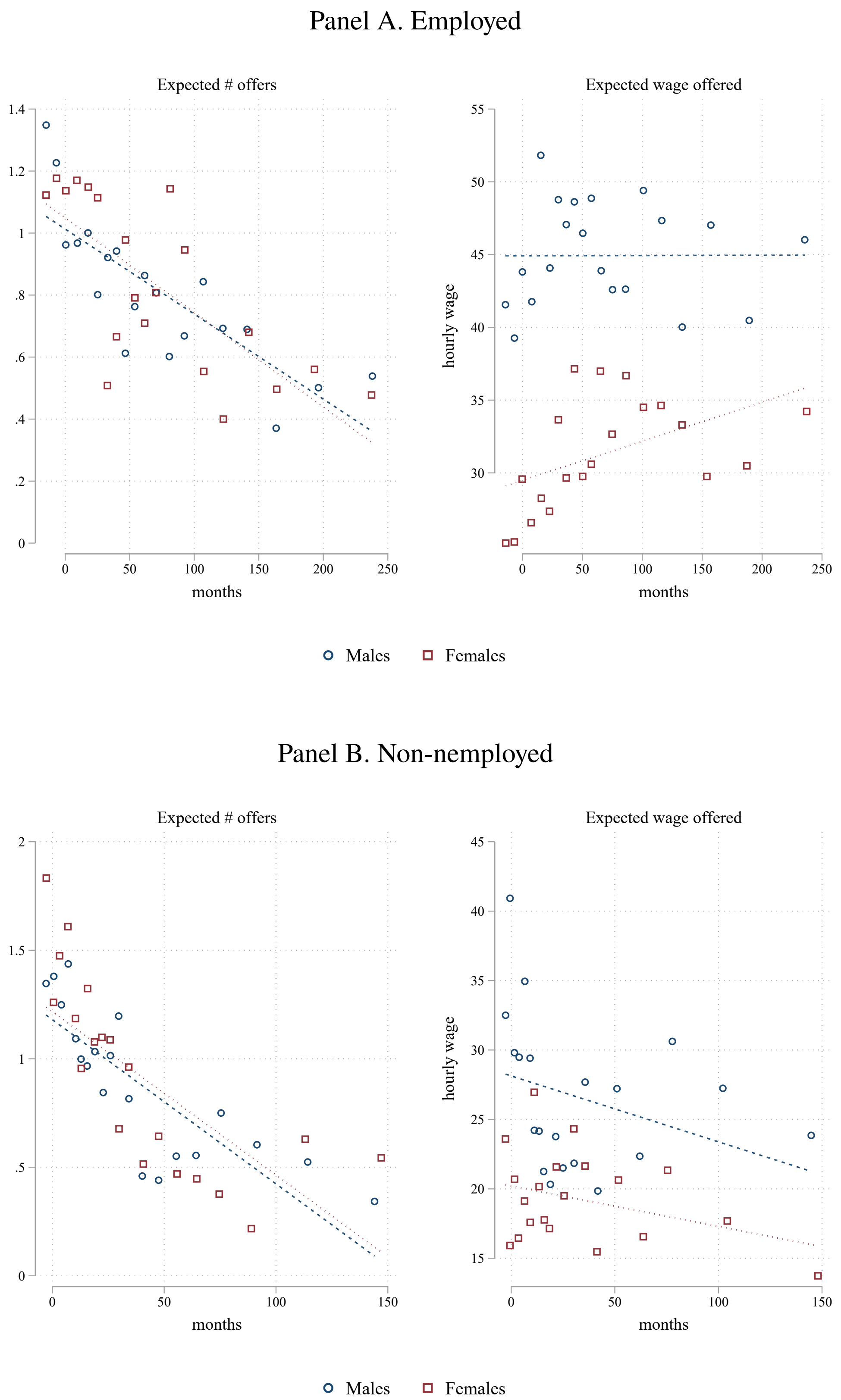

Figure A.2: Learning during job tenure and non-employment spell: Females vs. Males

Notes: Panel A and B are a binscatter of beliefs about number of offers (left) and wage offered (right) on the time workers spent employed or non-employed, in months, respectively. We control for a square polynomial in age and a dummy variables that equals to one if individuals report to be looking for a job. To account for outliers, we winsorize duration variables at the top 1% of the distribution. 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.

Table A.1: Expectations and Job Search Effort

	(1)	(2)	(3)	(4)
exp. best offer	-2.149		-1.510	12.190
	(2.412)		(2.016)	(12.078)
exp. # offers		8.552	8.534	45.940
		(8.138)	(8.123)	(44.743)
Observations	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.

B Theoretical Appendix

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

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

is the inflow of workers of type x_i to employment at jobs paying less than or equal to w at time t minus 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 $F(w|x_i)$ gives the c.d.f. of the observed wage distribution, conditional on worker characteristics:

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

Taking the derivative of the cdf we obtain the steady state pdf of the observed wage distribution conditional on worker characteristics:

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

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

$$\mathbb{E}_f[w|x_i] = \int_{R(x_i)}^{\infty} wf(w|x_i)\, dw \tag{B.4}$$

$$\mathbb{E}_f[w|x_i] = \frac{\delta(x_i)}{1 - G(R(x_i)|x_i)} \int_{R(x_i)}^{\infty} wg(w|x_i)\left[\frac{\delta(x_i) + \lambda_e(x_i)[1 - G(R(x_i)|x_i)]}{\{\delta(x_i) + \lambda_e(x_i)[1 - G(w|x_i)]\}^2}\right] dw. \tag{B.5}$$

C Estimation Appendix

C.1 Derivation of Distributions

This section derives all distributions used to construct the likelihood function described in Section 4 using the structural assumptions.

Number of offers We have assumed the arrival rate of job offers is, conditional on the error term, Piosson and that the error follows a gamma distribution, therefore, the probability of expecting to receive $n^B_{l,i}$ offers in labor market state $l \in \{u, e\}$ is

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

where Equation C.1 holds because

$$\int_0^\infty \lambda^a \exp(-b\lambda)\, d\lambda = \frac{\Gamma(a+1)}{b^{a+1}}. \qquad \text{(C.3)}$$

Therefore, the number of job offers follows a negative binomial distribution. The number of true arrivals is derived equivalently. From Equation C.2, the probability that individual i believes he/she will have at least one offer is

$$\begin{aligned}
P(p_{l,1} > 0|x_i) &= 1 - P(n^B_{l,1} = 0|x_i) \\
&= 1 - \left(\frac{1}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}x_i)}\right) \qquad \text{(C.4)}
\end{aligned}$$

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

$$\begin{aligned} P(\bar{W}_i^B \leq w | n_{l,i}^B, x_i) &= P(\max\{W_{i,1}^B, ..., W_{i,n_{l,i}^B}^B\} \leq w | n_{l,i}^B, x_i) \\ &= G^B(w; \mu_i^B, \sigma^B)^{n_{l,i}^B} \end{aligned} \tag{C.5}$$

and the pdf is

$$P(\bar{w}_i^B | n_{l,i}^B, x_i) = n_{l,i}^B G^B(\bar{w}_i^B; \mu_i^B, \sigma^B)^{(n_{l,i}^B - 1)} g^B(\bar{w}_i^B; \mu_i^B, \sigma^B) \tag{C.6}$$

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

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

$$\begin{aligned} P(\tilde{w}_i | n_{l,i}, x_i) = & [P(w_{i,1} | n_{l,i} = 1, x_i) P(n_{l,i} = 1 | x_i)]^{\mathbb{1}(n_{l,i}=1)} \\ & \times [P(w_{i,1}, w_{i,2} | n_{l,i} = 2, x_i) P(n_{l,i} = 2 | x_i)]^{\mathbb{1}(n_{l,i}=2)} \\ & \times [P(w_{i,1}, w_{i,2}, w_{i,3} | n_{l,i} \geq 3, x_i) P(n_{l,i} \geq 3 | x_i)]^{\mathbb{1}(n_{l,i} \geq 3)}, \end{aligned} \tag{C.7}$$

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

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

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

$$P(w_{i,1}, w_{i,2} | n_{l,i} = 2, x_i) = g(w_{i,1}; \mu_i, \sigma) \times g(w_{i,2}; \mu_i, \sigma). \tag{C.9}$$

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

$$P(w_{i,1}, w_{i,2}, w_{i,3} | n_{l,i} \geq 3, x_i) = (n_{l,i} - 2) G(w_{i,3}; \mu_i, \sigma)^{n_{l,i} - 3} \prod_{j=1}^{3} g(w_{i,j}; \mu_i, \sigma). \tag{C.10}$$

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 occur 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

$$P(s_i^B = 0|x_i) = \left(\frac{1}{1 + \theta_\delta^B \exp(\beta_3^B x_i)}\right)^{k_\delta^B}. \tag{C.11}$$

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 have assume separations to follow a Poisson process, the arrival time of shocks is distributed exponentially and $s_i^B = 1 - \exp(-\delta_i^B)$. The cdf of the believed separation probability is

$$\begin{aligned} P(s_i^B \leq s|x_i) &= P[1 - \exp(-\delta_i^B) \leq s] \\ &= P[1 - \exp(-\phi_i^B \exp(\beta_3^B x_i)) \leq s] \\ &= P\left(\phi_i^B \leq \frac{-\ln(1 - s_i^B)}{\exp(\beta_3^B x_i)}\right) \end{aligned} \tag{C.12}$$

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

$$p(s_i^B|x_i) = \frac{1}{\Gamma(k_\delta^B)[\theta_\delta^B \exp(\beta_3^B x_i)]^{k_\delta^B}} \frac{[-\ln(1 - s_i^B)]^{k_\delta^B - 1}}{1 - s_i^B} \exp\left(\frac{\ln(1 - s_i^B)}{\theta_\delta^B \exp(\beta_3^B x_i)}\right). \tag{C.13}$$

For workers that report $s_i^B = 1$ we subtract $2.2204e^{-16}$ such that Equation C.13 is real; 0.14% of the sample of women and 0.45% of the sample of men report a believed separation probability equal to 1.

Employment duration For employed workers, the duration of the employment spell. Each employment spell can end due to a move to another job or through exogenous separation. Denoting the rate at which workers leave their current job as $\eta_i = \delta_i + \lambda_{e,i}[1 - G(w_i^c; \mu_i, \sigma)]$. Since both separations to unemployment and separations to a new employer follow poisson processes, that are independent, the process for leaving the current employer also follows poisson process with rate η_i. Since η_i is the sum of two independent gamma variables, using the Welch-Satterwaite approximation we have that $\eta_i \sim_{approx} Gamma(k_\eta, \theta_\eta)$ where

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

$$\theta_\eta = \frac{k_\delta \left(\theta_\delta \exp(\beta_3 x_i)\right)^2 + k_{\lambda,e}\left(\theta_{\lambda,e} \exp(\beta_{e,1} x_i)[1 - G(w_i^c; \mu_i, \sigma)]\right)^2}{k_\delta \theta_\delta \exp(\beta_3 x_i) + k_{\lambda,e}\theta_{\lambda,e} \exp(\beta_{e,1} x_i)[1 - G(w_i^c; \mu_i, \sigma)]}. \tag{C.15}$$

Conditional on a single draw of η_i the process for leaving the current employer is poisson, and the unconditional number of arrivals is negative binomial, as shown above. So the probability of receiving no separation shocks (either to unemployment or new employment) over duration t is

$$P(N_\eta(t) = 0|x_i) = \left(\frac{1}{1+\theta_\eta t}\right)^{k_\eta} \tag{C.16}$$

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

When we observe an employment duration, d_i, we observe a right censored version of the full duration d_i^*, so the probability of observing employment duration of length d_i is

$$\begin{aligned} P(d_i|w_i^c, x_i) &= C[1 - P(N_\eta(d_i) = 0|x_i)] \\ &= C[1 - (1+\theta_\eta d_i)^{-k_\eta}] \end{aligned} \tag{C.17}$$

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

$$\begin{aligned} C^{-1} &= \int_0^\infty 1 - (1+\theta_\eta t)^{-k_\eta}\, dt \\ C^{-1} &= \frac{1}{\theta_\eta(k_\eta - 1)} \end{aligned} \tag{C.18}$$

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

$$P(d_i|w_i^c, x_i) = \theta_\eta(k_\eta - 1)[1+\theta_\eta d_i]^{-k_\eta}, \tag{C.19}$$

where k_η and θ_η are given by Equation C.14 and Equation C.15.

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

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

where R_i is the workers reported reservation wage.

Unemployment and Employment Probability Let u_i be an indicator that takes on the value 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

$$\mathbb{E}_\phi[\delta_i|x_i]P(u_i|x_i) = \{\mathbb{E}_\phi[\delta_i|x_i] + \mathbb{E}_\nu[\lambda_{u,i}][1 - G_i(R_i)]\}[1 - P(u_i|x_i)]. \tag{C.20}$$

Then the probability of observing worker i as unemployed is

$$P(u_i|x_i) = \frac{\mathbb{E}_\phi[\delta_i|x_i]}{\mathbb{E}_\phi[\delta_i|x_i] + \mathbb{E}_\nu[\lambda_{u,i}][1 - G_i(R_i)]}$$
$$= \frac{k_\delta \theta_\delta \exp(\beta_3 x_i)}{k_\delta \theta_\delta \exp(\beta_3 x_i) + k_{\lambda,u}\theta_{\lambda,u} \exp(\beta_{u,1} x_i)[1 - G(R_i; \mu_i, \sigma)]} \tag{C.21}$$

and the probability of observing the worker as employed is $P(e_i|x_i) = 1 - P(u_i|x_i)$.

C.2 Parameter Estimates

Table C.1: Estimated Job Arrival Rates

	Unemployed				Employed			
	Believed Arrival Rate		True Arrival Rate		Believed Arrival Rate		True Arrival Rate	
	Women	Men	Women	Men	Women	Men	Women	Men
Age	0.047	0.044	0.340	0.426	-0.012	0.027	-0.000	0.084
	(0.018)	(0.012)	(0.034)	(0.034)	(0.011)	(0.008)	(0.023)	(0.022)
Age^2	-0.001	-0.001	-0.005	-0.006	0.000	-0.000	-0.000	-0.001
	(0.024)	(0.012)	(0.028)	(0.001)	(0.127)	(0.007)	(0.052)	(0.005)
Married	-0.100	0.095	-0.475	-0.059	-0.079	-0.039	-0.323	-0.200
	(0.067)	(0.073)	(0.114)	(0.126)	(0.037)	(0.036)	(0.073)	(0.072)
Child	0.034	0.067	-1.066	0.361	0.080	-0.044	0.254	-0.030
	(0.078)	(0.094)	(0.127)	(0.159)	(0.040)	(0.036)	(0.078)	(0.073)
Some College	0.024	0.149	1.196	0.530	-0.068	0.073	-0.032	-0.250
	(0.075)	(0.084)	(0.143)	(0.150)	(0.046)	(0.045)	(0.096)	(0.087)
College	0.015	0.170	0.224	0.262	-0.087	0.054	0.459	-0.177
	(0.085)	(0.098)	(0.147)	(0.160)	(0.050)	(0.045)	(0.100)	(0.085)
Advanced Degree	-0.170	0.193	0.721	0.870	-0.051	-0.002	0.509	-0.040
	(0.120)	(0.113)	(0.190)	(0.183)	(0.058)	(0.051)	(0.119)	(0.086)
Race-Black	0.467	0.344	-0.002	0.366	0.240	0.333	0.239	0.682
	(0.090)	(0.122)	(0.193)	(0.239)	(0.055)	(0.071)	(0.111)	(0.123)
Race-Other	0.147	-0.281	0.023	0.619	0.056	0.099	0.213	0.040
	(0.091)	(0.132)	(0.164)	(0.200)	(0.053)	(0.046)	(0.100)	(0.092)
High Ability	-0.005	-0.329	0.244	-0.635	-0.005	0.022	-0.270	-0.229
	(0.068)	(0.076)	(0.116)	(0.144)	(0.040)	(0.042)	(0.077)	(0.078)
Searching	0.871	0.798	-0.078	-0.676	0.870	0.678	0.724	0.787
	(0.065)	(0.077)	(0.127)	(0.122)	(0.034)	(0.033)	(0.073)	(0.063)
k	9.950	75.299	0.050	0.047	15.929	162.310	1.046	1.158
	(2.250)	(28.158)	(0.005)	(0.006)	(3.198)	(66.522)	(0.047)	(0.033)
θ	0.049	0.009	0.224	0.213	0.081	0.004	0.303	0.087
	(0.022)	(0.004)	(0.161)	(0.152)	(0.024)	(0.002)	(0.142)	(0.040)

Table C.2: Estimated Wage Offer Distribution

	Believed Offer Dist.		True Offer Dist.	
	Women	Men	Women	Men
Age	0.028	0.048	0.010	-0.000
	(0.008)	(0.008)	(0.009)	(0.007)
Age^2	-0.000	-0.001	-0.000	0.000
	(0.022)	(0.000)	(0.138)	(0.005)
Married	0.206	0.195	0.192	0.231
	(0.024)	(0.028)	(0.024)	(0.027)
Child	-0.079	0.032	-0.070	-0.036
	(0.026)	(0.028)	(0.026)	(0.025)
Some College	-0.180	-0.003	-0.442	-0.273
	(0.029)	(0.033)	(0.033)	(0.032)
College	0.288	0.480	0.362	0.538
	(0.034)	(0.033)	(0.034)	(0.031)
Advanced Degree	0.506	0.793	0.519	0.707
	(0.038)	(0.037)	(0.040)	(0.034)
Race-Black	-0.131	-0.138	-0.085	-0.175
	(0.034)	(0.046)	(0.039)	(0.047)
Race-Other	0.093	-0.102	0.015	-0.130
	(0.031)	(0.028)	(0.034)	(0.031)
High Ability	0.187	0.192	0.153	0.147
	(0.025)	(0.030)	(0.027)	(0.028)
Searching	-0.138	-0.168	-0.105	-0.069
	(0.023)	(0.023)	(0.025)	(0.023)
Constant	0.684	0.329	0.643	0.793
	(0.161)	(0.172)	(0.165)	(0.150)
σ	0.559	0.568	0.638	0.652
	(0.009)	(0.008)	(0.008)	(0.007)

Table C.3: Estimated Job Separation Rates

	Believed Separation Rate		True Separation Rate	
	Women	Men	Women	Men
Age	-0.167	-0.287	-0.161	-0.111
	(0.034)	(0.022)	(0.014)	(0.011)
Age^2	0.002	0.004	0.002	0.001
	(0.013)	(0.005)	(0.002)	(0.007)
Married	-0.073	0.096	-0.128	-0.100
	(0.095)	(0.076)	(0.050)	(0.051)
Child	0.516	-0.381	0.065	-0.137
	(0.103)	(0.089)	(0.053)	(0.050)
Some College	0.389	0.221	-0.014	0.104
	(0.121)	(0.094)	(0.059)	(0.057)
College	0.687	-0.100	-0.074	0.132
	(0.137)	(0.094)	(0.070)	(0.060)
Advanced Degree	-0.348	-0.180	0.069	0.266
	(0.156)	(0.102)	(0.082)	(0.065)
Race-Black	-0.015	-0.469	0.025	0.285
	(0.144)	(0.166)	(0.080)	(0.101)
Race-Other	0.097	-0.023	0.093	0.057
	(0.142)	(0.106)	(0.070)	(0.065)
High Ability	0.191	-0.138	-0.122	-0.198
	(0.109)	(0.083)	(0.050)	(0.055)
Searching	0.078	-0.010	0.428	0.397
	(0.104)	(0.088)	(0.057)	(0.055)
k	0.364	0.382	9.812	149.467
	(0.016)	(0.014)	(1.863)	(61.323)
θ	5.782	28.377	0.308	0.006
	(3.957)	(12.577)	(0.101)	(0.002)

Table C.4: Estimated Flow Value of Unemployment

	Women	Men
Age	0.180	0.160
	(0.028)	(0.036)
Age^2	-0.002	-0.001
	(0.000)	(0.001)
Married	0.684	1.237
	(0.280)	(0.413)
Child	-0.721	-2.193
	(0.334)	(0.694)
Some College	-0.870	-0.732
	(0.309)	(0.481)
College	2.076	2.979
	(0.405)	(0.640)
Advanced Degree	4.377	6.616
	(0.548)	(0.878)
Race-Black	0.032	-0.895
	(0.374)	(0.722)
Race-Other	-0.306	2.916
	(0.350)	(0.944)
High Ability	1.113	1.344
	(0.275)	(0.449)
Searching	-1.286	-2.041
	(0.273)	(0.455)
Constant	0.118	-0.146
	(0.066)	(0.080)
R-squared	0.284	0.216
Observations	901	848

D Counterfactual Appendix

D.1 Derivation of the Bias in Beliefs

For all counterfactual, we define *bias* as the expected percent difference between the true and believed parameters, that is the difference between the expected value of the predicted logged believed and logged true parameters of the model. In what follows, we provide details on how we compute the bias in beliefs about each parameter.

Job arrival and separation rates For a worker of type x_i, the bias in the log arrival rates is then given by,

$$\begin{aligned} bias_{\lambda_{l,M}}(x_i) &= \mathbb{E}[\ln \hat{\lambda}^B_{l,M}(x_i)] - \mathbb{E}[\ln \hat{\lambda}_{l,M}(x_i)] \\ &= (\hat{\beta}^B_{l,1,M} - \hat{\beta}_{l,1,M}) \times x_i + \psi(\hat{k}^B_{\lambda,l,M}) - \psi(\hat{k}_{\lambda,l,M}) + \ln \hat{\theta}^B_{\lambda,l,M} - \ln \hat{\theta}_{\lambda,l,M}, \end{aligned} \tag{D.1}$$

where the subscript M indicated the estimates for men, and ψ is the digamma function.[11] The bias in the separation rates follow an identical structure.

Offer distribution The bias in the mean offer distribution is defined as

$$\begin{aligned} bias_{\mu_M}(x_i) &= \mathbb{E}[\ln \hat{w}^B_{i,M}] - \mathbb{E}[\ln \hat{w}_{i,M}] \\ &= (\hat{c}^B_{2,M} - \hat{c}_{2,M}) + (\hat{\beta}^B_{2,M} - \hat{\beta}_{2,M}) \times x_i, \end{aligned} \tag{D.2}$$

and the bias in the variance of the offer distribution is defined as,

$$bias_{\sigma_M} = \ln \sigma^B_M - \ln \sigma_M. \tag{D.3}$$

[11]The expected value of $\ln \nu \sim \ln Gamma(k, \theta)$ is $\psi(k) + \ln \theta$, where ψ is the digamma function defined as $\psi(x) = d \ln \Gamma(x)/dx$.