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Labor Market Beliefs and the Gender Wage Gap

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Abstract

We study how labor market beliefs shape the gender wage gap in an equilibrium search model with endogenous wage setting and hiring, in which workers hold subjective expectations about wage offers, job arrival rates, and separation risk. Using data from the Survey of Consumer Expectations to estimate the model, we find that gender differences in beliefs account for 25% of the gender wage gap. Correcting these beliefs partly narrows the gap but is not welfare-improving, as it reduces lifetime earnings for both men and women. In contrast, equalizing labor market fundamentals substantially reduces the wage gap while increasing women's lifetime earnings.

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1 Introduction

When individuals decide whether to accept a job offer, their expectations about various labor market outcomes—such as the likelihood of finding a new job—play a central role. However, these expectations are often biased: individuals tend to be overly optimistic about both job-finding probabilities and wage offers (see Mueller and Spinnewijn (2023) for a review). Importantly, these biases differ across genders. Among college graduates, men tend to be more optimistic than women about future wage offers, contributing to gender differences in reservation wages (Cortés et al., 2023; Kiessling et al., 2024). These findings suggest that gender differences in labor market expectations may be an important, yet underexplored, driver of the gender wage gap.

This paper aims to quantify the role of subjective expectations in shaping gender wage inequality. To do so, we incorporate subjective expectations into the job-ladder framework of Burdett and Mortensen (1998), building on extensions of Engbom and Moser (2022) and Morchio and Moser (2024) that also allow for endogenous hiring. Through the lens of the model, we find that gender differences in beliefs account for approximately 25% of the gender wage gap. Correcting beliefs partly closes the gap, but is not welfare-improving: as reservation wages decrease, firms respond by offering lower wages, reducing lifetime earnings for both men and women. In contrast, equalizing labor market fundamentals, substantially narrows the wage gap while increasing women's lifetime earnings.

In the model, workers differ in their gender and ability and engage in random search in frictional labor markets segmented by worker type. Firms differ in their productivity and choose what wage to offer and a recruiting intensity in each market. Workers may hold biased beliefs about future wage offers, offer arrival rates, and separation probabilities. In equilibrium, these beliefs shape realized wages through their effect on reservation wages. For instance, workers who overestimate the likelihood of receiving a job offer perceive the value of remaining nonemployed to be higher than it actually is, leading them to set higher reservation wages and be more selective about job offers. While this raises accepted wages, it also prolongs nonemployment spells.

We estimate model parameters using data from the Survey of Consumer Expectations and its Labor Market Survey supplement, focusing on working-age individuals between 2015 and 2019. The panel survey provides standard information on employment and wages, as well as a set of questions designed to capture expectations about future job opportunities and wage offers. In the data, both men and women overestimate job offers and wages over a four-month horizon, but with different patterns: men are more optimistic about wages, while women overestimate offer arrival by more. Consistent with the model, wage offer expectations are positively associated with reservation wages, explaining approximately 64% of the gender gap in reservation wages, a result robust to controlling for risk aversion.

To bring the model to the data while accounting for worker heterogeneity, we specify model parameters as functions of worker type, mapped to a set of worker characteristics that matter for empirical wage dispersion. This allows us to control for compositional differences not only in wages but also in arrival and separation rates, and to focus the counterfactual analysis on the residual wage gap. Decomposing this residual wage gap, we find that gender differences in beliefs account for approximately 25%, while differences in labor market parameters explain 88%, with the value of nonemployment slightly offsetting the other two channels. Allowing for gender differences in risk aversion reduces the role of beliefs, which nonetheless remains substantial, at approximately 18% of the residual gap.

We then conduct two policy-relevant counterfactuals. Our first counterfactual corrects beliefs about labor market parameters for both men and women, reducing the residual wage gap by about 16 percentage points. Since both men and women are optimistic, aligning beliefs with true labor market conditions lowers their perceived value of nonemployment, reducing reservation wages. Firms react by shifting down their offer distribution and posting more vacancies. As a result, average wages fall for both genders. The effect is more pronounced for men, who are more optimistic, driving the reduction in the wage gap. However, the correction has an unintended effect: lower wages translate into lower lifetime earnings for both men and women, so while the gap narrows, both groups are worse off in absolute terms. When we correct only beliefs about the wage offer distribution, mimicking a pay transparency policy, the wage gap falls modestly by about 1.8 percentage points (7.3%), consistent with recent empirical evidence on pay transparency laws (Duchini et al., 2022; Bennedsen et al., 2022; Gulyas et al., 2021).

Our second counterfactual equalizes labor market parameters, namely firm productivity, separation rates, and search intensity, by giving women the same values as men while keeping their beliefs unchanged. This reduces the gender wage gap by 86%, with the composite productivity distribution being the primary driver, and raises women's lifetime earnings, closing the lifetime earnings gap. The estimated gender differences in composite productivity capture different underlying mechanisms that generate wage disparities, including differences in firm productivity (Card et al., 2016), taste-based discrimination (Becker, 1971; Flabbi, 2010), and gender-specific preferences for non-wage attributes (Goldin, 2014). While separately identifying these channels is beyond the scope of this paper, the results highlight the key role of the mechanisms shaping where men and women work in driving the gender wage gap, consistent with recent findings (Morchio and Moser, 2024; Faberman et al., 2025).

Overall, these results speak to the broader debate on how to close the gender wage gap. Correcting beliefs narrows the gap, but leaves both men and women worse off in terms of lifetime earnings. Instead, addressing the mechanisms that sort women into lower-paying firms, whether stemming from firm pay premiums, taste-based discrimination or gender-specific preferences for non-wage amenities, is not only more effective at closing the gender wage gap, but also yields welfare gains for women.

Related literature Our findings contribute to the literature analyzing gender differences in job search behavior and outcomes. Specifically, our work builds on the literature that studies the gender wage gap through the lens of equilibrium search models (e.g. Bowlus, 1997; Flabbi, 2010; Liu, 2016; Amano-Patino et al., 2020; Flinn et al., 2020; Xiao, 2021; Morchio and Moser, 2024; Faberman et al., 2025). A common assumption in this literature is that individuals have rational expectations, implying that they know their labor market prospects. To the best of our knowledge, this paper is the first to incorporate subjective beliefs into a job search framework to study gender differences in labor market outcomes. By doing so, we shed light on the transmission of expectations to wages and their implications for the gender wage gap. A further contribution relative to the existing literature concerns the treatment of worker heterogeneity. Most prior studies estimate search parameters separately by gender and other covariates by splitting the sample, which restricts the number of covariates one can accommodate while maintaining a sufficient sample size within each subgroup. Rather than splitting the sample, we specify all model parameters, including arrival rates, separation rates, and their belief counterparts, as functions of a broad set of observable characteristics, as in Flinn et al. (2020). This allows us to account for compositional differences along a richer set of dimensions without sacrificing sample size, and ensures that estimated gender differences in labor market parameters are not confounded by compositional differences in who is searching.

Our work is also related to empirical studies documenting gender differences in wage expectations among college graduates , female students exhibit lower levels of overoptimism (Reuben et al., 2017; Cortés et al., 2023; Kiessling et al., 2024). By embedding subjective expectations into a canonical search model, we complement this literature in two ways: we show that gender differences in beliefs extend beyond college graduates, and we quantify their role in driving the gender wage gap. In doing so, we find that while beliefs contribute to the gap, correcting them alone has a far smaller effect than moving to a gender-neutral labor market, and comes with an unintended consequence of reducing lifetime earnings for both men and women.

Finally, we contribute to a growing literature on the role of biased expectations in labor markets. Mueller et al. (2021) show that optimistic job-finding beliefs reduce search effort, while Conlon et al. (2018) highlight the role of wage expectations in shaping reservation wages. Closely related, Balleer et al. (2024) link biased expectations to regional wage disparities. We extend this literature by jointly modeling beliefs about wages, job offer arrival rates, and separation risks, and by quantifying how gender differences in these beliefs translate into gender wage inequality.

2 Model

We develop an equilibrium search model in which workers hold beliefs about labor market parameters, such as arrival rates, wage offers, and separation rates, that deviate from the true parameters. Our framework builds on the canonical job-ladder model of Burdett and Mortensen (1998), extended by Engbom and Moser (2022) and Morchio and Moser (2024) to incorporate unobserved worker heterogeneity and endogenous job creation in a tractable manner.

2.1 Workers

There is a continuum of risk-neutral workers that share the same discount rate r. They differ in their gender $g \in \{f, m\}$ and ability a, with associated measure $\mu_{ga} \geq 0$ satisfying $\sum_g \int_a \mu_{ga} da = 1$. At any point in time, a worker is either employed or nonemployed, with $j \in \{e, u\}$ denoting their employment status. Nonemployment includes workers who are either unemployed or not in the labor force, which we take into account when we calibrate our model.

Job Search As in Morchio and Moser (2024) and Engbom and Moser (2022), among others, labor markets are segmented by worker type so that each worker searches for jobs within a market defined by their gender g and ability a. When non-employed, a worker of type (g, a) receives a flow value of nonemployment $b(g, a)$ and meets firms at rate $\lambda_u(g, a)$. When employed, a worker earns a wage w and receives job offers at rate $\lambda_e(g, a) = s(g, a)\lambda_u(g, a)$, where $s(g, a)$ denotes the relative on-the-job search intensity. Wage offers are drawn from the distribution $F(w \mid g, a)$. Matches dissolve either endogenously, when an employed worker accepts an outside offer at a higher wage, or exogenously through layoffs, which arrive at rate $\delta(g, a)$

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

Reservation Wage For a nonemployed worker of type (g, a), the reservation wage R_{ga} is the wage offer at which the worker is indifferent between accepting and rejecting an offer, given their beliefs. Thus, it satisfies $E^B(R(g, a), g, a) = U^B(g, a)$, where $E^B(w, g, a)$

is the perceived value of employment at wage w and $U^B(g,a)$ is the perceived value of nonemployment. The perceived value of nonemployment is given by

$$rU^B(g,a) = b(g,a) + \lambda_u^B(g,a) \int_{R_{ga}}^{\bar{w}} \left[E^B(w,g,a) - U^B(g,a)\right] dF^B(w \mid g,a), \qquad (1)$$

where $b(g,a)$ is the flow value of nonemployment, and $\lambda_u^B(g,a)$ and $F^B(w|g,a)$ are, respectively, the worker's beliefs about the job arrival rate and the wage offer distribution. Analogously, the perceived value of an employed worker of type (g,a) in a job with wage w is

$$\begin{aligned} rE^B(w,g,a) = w + \lambda_e^B(g,a) \int_{w}^{\bar{w}} \left[E^B(w',g,a) - E^B(w,g,a)\right] dF^B(w' \mid g,a) \qquad (2) \\ + \delta^B(g,a)\left[U^B(g,a) - E^B(w,g,a)\right]. \end{aligned}$$

where $\lambda_e^B(g,a)$, $\delta^B(g,a)$ and $F^B(w|g,a)$ are, respectively, the worker's beliefs about the job arrival rate on-the-job, likelihood of separation, and the wage offer distribution.[1] Using these definitions, the reservation wage R_{ga} for an unemployed worker of type (g,a) satisfies

$$R_{ga} = b(g,a) + \left[\lambda_u^B(g,a) - \lambda_e^B(g,a)\right] \int_{R_{ga}}^{\bar{w}} \frac{1 - F^B(w \mid g,a)}{r + \delta^B(g,a) + \lambda_e^B(g,a)\left[1 - F^B(w \mid g,a)\right]} dw. \qquad (3)$$

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

[1] As in Morchio and Moser (2024), we assume no on-the-job wage dynamics: wages remain constant at w during an employment spell, and any wage changes occur only through job-to-job transitions. This assumption is motivated by the structure of the SCE data, which we use to estimate the model: each respondent participates for up to 12 months, and all questions refer to annual earnings, making it difficult to identify within-job wage growth.

(falls). Employed workers in a job with wage w accept any job that offers a higher wage.

Employment Distribution Let $G(w \mid g, a)$ denote the steady-state cumulative distribution function of employed workers of type (g, a) over wages w. Appendix B.2 shows that this distribution satisfies

$$G(w \mid g, a) = \frac{\lambda^u(g,a)F(w \mid g,a)}{\delta(g,a) + \lambda_e(g,a)[1 - F(w \mid g,a)]} \cdot \frac{u_{ga}}{1 - u_{ga}} \tag{4}$$

Nonemployment The steady-state nonemployment rate for each worker type (g, a) is

$$u_{ga} = \frac{\delta(g,a)}{\delta(g,a) + \lambda_u(g,a)}. \tag{5}$$

2.2 Firms

Firms are heterogeneous in their productivity $p \in [\underline{p}, \bar{p}]$ and a set of gender wedges $z_{g,a} \in [\underline{z}, \bar{z}]$, representing the firm's disutility from worker type (g, a) as in Morchio and Moser (2024) and Becker (1971). Thus, a firm's type is $j = (p, \{z_{ga}\}_{ga})$, which we assume is continuously distributed according to $\Gamma(j)$.

Production and Hiring A firm with productivity p employing $\{l_{ga}\}_{ga}$ workers of each type produces output according to the following linear production technology:

$$y\left(p, \{l_{ga}\}_{ga}\right) = p \sum_g \int_a a\, l_{ga}\, da. \tag{6}$$

To hire workers, a firm posting $v \geq 0$ vacancies for workers of type (g, a) pays a flow cost

$$c^v(v_{ga}) = c\frac{v_{ga}^{1+\eta}}{1+\eta} \tag{7}$$

where $c > 0$ is a vacancy cost shifter and $\eta > 0$ governs the elasticity of vacancy costs with respect to the number of vacancies posted. Firms post wages and vacancies in each market to maximize their steady-state flow payoff.

Value Function The value $\Pi(j)$ of a firm of type j is given by

$$r\Pi(j) = \max_{w_{ga}, v_{ga}} \sum_g \int_a [pa - w_{ga} - z_{ga}] l_{ga}(w_{ga}, v_{ga}) - c^v(v_{ga}) da \tag{8}$$

where $l_{ga}(w_{ga}, v_{ga})$ is the number of workers of type (g, a) that a firm posting wage w and vacancies v attains in equilibrium.

2.3 Matching

The total mass of vacancies posted in market (g, a) across firm types j is given by

$$V_{ga} = M \int_j v_{ga}(j) d\Gamma(j), \quad \forall (g, a) \tag{9}$$

where M is the mass of firms. The effective mass of job searchers in market (g, a) is given by

$$U_{ga} = \mu_{ga}[u_{ga} + s(g, a)(1 - u_{ga})], \quad \forall (g, a) \tag{10}$$

where u_{ga} is the steady-state nonemployment rate (Equation 5), μ_{ga} is the mass of workers of type (g, a), and $s(g, a)$ is the relative hazard of nonemployed to employed job seekers. A Cobb-Douglas matching function with constant returns to scale combines the mass of job searchers with the mass of job vacancies to produce m_{ga} matches between workers and firms according to

$$m_{ga} = \chi_{ga} V_{ga}^{\alpha} U_{ga}^{(1-\alpha)}, \quad \forall (g, a) \tag{11}$$

where $\chi_{ga} > 0$ is the matching efficiency and $\alpha \in (0, 1)$ is the matching elasticity with respect to aggregate vacancies. Labor market tightness is

$$\theta_{ga} = \frac{V_{ga}}{U_{ga}}, \quad \forall (g, a). \tag{12}$$

The *true* job-finding rates among nonemployed workers, $\lambda_u(g, a)$; the job-finding rates among the employed, $\lambda_e(g, a)$; and firms' job-filling rates, q_{ga}, are given by

$$\lambda_u(g, a) = \chi_{ga} \theta_{ga}^{\alpha}, \quad \lambda_e(g, a) = s(g, a)\lambda_u(g, a), \quad q_{ga} = \chi_{ga} \theta_{ga}^{(\alpha-1)}, \quad \forall (g, a). \tag{13}$$

2.4 Firm Size Distribution

The law of motion of employment at a firm offering wage w and posting v vacancies, given the wage offer distribution $F(w \mid g, a)$ and labor market tightness θ_{ga}, is

$$\dot{l}_{ga}(w, v) = -(\delta(g, a) + \lambda_e(g, a)[1 - F(w|g, a)])l_{ga}(w, v) \\ + vq_{ga}\left(\frac{u_{ga} + s(g, a)\left(1 - u_{ga}\right)G(w \mid g, a)}{u_{ga} + s(g, a)\left(1 - u_{g,a}\right)}\right). \tag{14}$$

Firms lose workers either to nonemployment or to higher-paying firms up the job ladder. Each vacancy contacts a potential hire at rate q_{ga}, the contacted worker is nonemployed with probability $u_{ga}/\left[u_{ga} + s(g, a)(1 - u_{ga})\right]$ and employed with complementary probability. An employed worker accepts the offer only if their current employer pays less than w.

Solving for the steady-state firm size distribution in market (g, a) by setting $\dot{l}_{ga}(w, v) = 0$ and substituting $G(w \mid g, a)$, steady-state employment at a firm offering wage w and posting v vacancies is

$$l_{ga}(w, v) = \frac{v_{ga}u_{ga}\lambda_u(g, a)\mu_{ga}}{V_{ga}} \cdot \frac{\delta(g, a) + \lambda_e(g, a)}{\left(\delta(g, a) + \lambda_e(g, a)\left[1 - F(w|g, a)\right]\right)^2}. \tag{15}$$

2.5 Equilibrium

Firms choose wages and vacancies to maximize profits (Equation 8). As shown in Appendix B.2, the equilibrium in each market (g, a) is characterized by a system of two first-order ordinary differential equations governing the optimal wage and vacancy policies:

$$cv_{ga}^{\eta} = (pa - w_{ga} - z_{ga})\frac{u_{ga}\,\lambda_u(g, a)\,\mu_{ga}}{V_{ga}} \cdot \frac{\delta(g, a) + \lambda_e(g, a)}{\left(\delta(g, a) + \lambda_e(g, a)\left[1 - F(w|g, a)\right]\right)^2} \tag{16}$$

$$\delta(g, a) + \lambda_e(g, a)\left[1 - F(w|g, a)\right] = 2\lambda_e(g, a)\,f(w|g, a)\,(pa - w_{ga} - z_{ga}). \tag{17}$$

We define a firm's *composite productivity* $\tilde{p}$ in market (g, a) as $\tilde{p}_{ga} = pa - z_{ga}$, that is, productivity p net of the gender wedge z_{ga}.[2] A firm is profitable and active in any market

[2]Since the firm's profit function is additively separable across markets (g, a), composite productivity $\tilde{p}_{g,a} = pa - z_{ga}$ is a sufficient statistic for a firm's type *within* market (g, a). Our model is therefore isomorphic, market by market, to a standard Burdett and Mortensen (1998) model without gender wedges but with productivity p replaced by $\tilde{p}_{ga}$.

if and only if $\tilde{p}_{ga} \geq R_{ga}$. Let $v_{ga}(\tilde{p})$ and $w_{ga}(\tilde{p})$ denote the optimal vacancy and wage policies of a firm with composite productivity $\tilde{p}$ in market (g, a), respectively. Given these policies, the equilibrium wage offer distribution satisfies

$$F(w(\tilde{p}_{ga}) \mid g, a) = \frac{M}{V_{ga}} \int_{\tilde{p}' > R(ga)}^{\tilde{p}_{ga}} v_{ga}(\tilde{p}') d\Gamma(\tilde{p}') \tag{18}$$

so that $F(w(\tilde{p}_{ga}) \mid g, a)$ is the vacancy-weighted distribution of wages across active firms in market (g, a). Defining $h(\tilde{p}_{ga}) \equiv F(w(\tilde{p}_{ga})|g, a)$, the equilibrium distribution of vacancies — and in turn the equilibrium wage offer distribution — is governed by the differential equation

$$\begin{aligned} h'(\tilde{p}_{ga}) &= \frac{M\gamma_{ga}(\tilde{p}_{ga})}{V_{ga}} \\ &\times \left[\frac{u_{ga}\, \lambda_u(g, a)\, \mu_{g,a}\, (\delta(g, a) + \lambda_e(g, a))}{c\, V_{g,a}} \int_{R(ga)}^{\tilde{p}_{ga}} \left(\frac{1}{\delta(g, a) + \lambda_e(g, a)\, [1 - h(x)]} \right)^2 dx \right]^{\frac{1}{\eta}}. \end{aligned} \tag{19}$$

where $\gamma_{ga}(\tilde{p}_{ga})$ is the marginal density of composite productivity $\tilde{p}_{ga}$. The full derivation is provided in Appendix B.2.

Sources of gender wage differences Wage differences between men and women in our model arise through three distinct channels. The first channel operates through *beliefs*. Workers make job acceptance decisions based on their beliefs rather than true labor market parameters. As shown in Equation 3, the reservation wage $R(g, a)$ depends on believed arrival rates $\lambda_u^B(g, a)$ and $\lambda_e^B(g, a)$, the believed separation rate $\delta^B(g, a)$, and the believed wage offer distribution $F^B(w \mid g, a)$. Importantly, from Equation 19, beliefs affect observed wages *solely* through the reservation wage: beliefs affect the perceived value of job search, thereby shifting the minimum wage workers are willing to accept. This belief channel is the novel mechanism through which our model generates a gender wage gap, absent in job-ladder models with perfect information (Morchio and Moser, 2024).

The second channel operates through gender differences in *true labor market parameters*. Akin to classical job-ladder models (Burdett and Mortensen, 1998), gender differences in arrival rates, $\lambda_u(g, a)$ and $\lambda_e(g, a)$, and separation rates $\delta(g, a)$ govern the speed at which men and women climb their respective job ladders. If women are concentrated at lower rungs of the job ladder—due to higher separation rates or lower on-the-job arrival rates—they earn lower wages on average, generating a wage gap even in the absence of belief differences (Bowlus, 1997).

The third channel operates through gender differences in the *distribution of composite productivity* $\gamma(\tilde{p}_{ga})$. Since wages and vacancy creation are both strictly increasing in composite productivity, women facing a less favorable distribution $\gamma(\tilde{p}_{ga})$ receive fewer and lower wage offers in equilibrium, generating a wage gap independent of any differences in beliefs or search frictions.

2.6 Discussion of Model Assumptions

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

Second, we assume no interdependence between labor market beliefs and their true counterpart. We provide three pieces of evidence in support of this assumption. First, Appendix Table A.6 shows that workers' expectations are not significantly correlated with job search effort, suggesting a weak link between expectations and future realizations. Consistently, Adams-Prassl et al. (2023) show that workers perceive a low return to additional hours of search, lending support to the common practice of assuming constant finding rates (e.g. Mueller et al., 2021). Second, Appendix Figure A.1 shows that once individual fixed effects are included, lagged beliefs have no statistically significant predictive power for future realizations, suggesting that any correlation between beliefs and outcomes is driven by time-invariant individual heterogeneity rather than private information that may be systematically reflected in beliefs about labor market parameters. Third, Appendix C.5 shows that perfect correlation between beliefs and true labor market parameters is strongly rejected against a model that allows them to be independent. Taken together, this evidence supports the assumption that expectations affect wages through the reservation wage rather than true labor market parameters.

Third, we assume firms make "take-it-or-leave-it" offers, leaving no scope for wage bargaining. This assumption aligns well with the data used to estimate the model, where approximately 70% of respondents report receiving "take-it-or-leave-it" offers rather than engaging in negotiations over pay. Importantly, when estimating the model, we allow the distribution of composite productivity $\gamma(\tilde{p})$ to vary by gender. This approach implicitly captures gender-specific employer pay components that may arise from differences in bargaining (Card et al., 2016; Biasi and Sarsons, 2021; Roussille, 2024), but also taste-based discrimination (Becker, 1971; Flabbi, 2010), or gender-specific preferences for job attributes (Rosen, 1986; Goldin, 2014; Morchio and Moser, 2024; Faberman et al., 2025).

Finally, we abstract from belief updating, both regarding the arrival rate of offers and the offer distribution. Although Conlon et al. (2018) show that workers' expectations respond to wage offers, whether updating beliefs about the offer distribution affects the reservation wage depends on the gap between the arrival rates of offers while unemployed and employed, as shown in Equation 3. If $\lambda_u^B = \lambda_e^B$, the reservation wage becomes independent of beliefs about the wage offer distribution, in particular. In our estimates, λ_u^B and λ_e^B are very similar for both men and women (Table 3), suggesting that beliefs about the wage offer distribution have little effect on reservation wages, and therefore on the gender wage gap, as confirmed by the counterfactual analysis in Section 5. Additionally, Mueller et al. (2021) show that job seekers report roughly constant job-finding probabilities over time.[3]

[3] He and Kircher (2025) find that job seekers expect lower job-finding probabilities as unemployment duration increases, but revise their expectations upward (downward) when aggregate unemployment is unexpectedly low (high), which may explain Mueller et al. (2021)'s finding that average reported job-finding probabilities remain relatively stable during an unemployment spell. While it is interesting to explore the mechanisms behind this behavior, as long as perceived job-finding probabilities remain approximately constant over the spell, abstracting from belief updating seems a plausible simplification.

3 Data and Descriptive Evidence

3.1 Sources and Variables

We estimate the model using data from the Survey of Consumer Expectations (SCE) and its supplement, the Labor Market Survey (LMS), covering the period from November 2015 to November 2019. The SCE surveys a representative sample of around 1,300 US household heads on a monthly basis, with each individual participating for up to 12 months. Active panel members—those who completed the SCE in the previous three months—are eligible for the LMS, allowing up to three inclusions in the supplement during their tenure. The LMS is well-suited for our analysis as it collects information on job search behavior, beliefs about job offers and wages, reservation wages, and labor market outcomes such as employment duration and current wages. Demographic data are also available for respondents through the SCE survey. We restrict the sample to individuals aged between 20 and 65 with non-missing data on key variables and wages above $4/hr for current job, offers, and expectations, yielding 7,976 observations from 4,197 unique individuals, with men making up slightly more than half the sample. Appendix A.1 describes the sample and shows that it aligns well with the demographic characteristics of household heads in the Current Population Survey (CPS) over the same period.

Labour Market Status We classify respondents as employed if they worked for pay at the time of the survey, and as nonemployed otherwise, excluding those permanently unable to work. This definition is broader than the CPS definition, which restricts job seekers to those actively searching in the past four weeks. We adopt it following Braun (2024), who shows that hires from individuals classified as out of the labor force have risen substantially in recent decades.[4]

Labor Market Beliefs and Outcomes The LMS reports both beliefs and realizations about labor market outcomes. Respondents who report a positive probability of receiving at least one offer in the next four months are asked how many offers they expect and what is the best wage they expect to be offered. We use these answers to discipline the believed

[4]Consistently, around two-thirds of respondents in our sample who would be classified as out of the labor force under CPS criteria report a positive probability of receiving a job offer or being employed within four months.

arrival rates and offer distribution. Separately, all respondents report the number of offers actually received and the salaries of the three best offers over the past four months, which we use to infer true arrival rates and offer distribution. The LMS also asks employed respondents about the probability of being unemployed, whether looking for work or not, four months from the survey date which we use as our measure of perceived job separation probability.[5] We also observe actual monthly transitions to nonemployment in the SCE and use employment durations to calibrate the true separation rate. For employed respondents, the survey reports their current wage, employment duration, and industry. Finally, the LMS elicits reservation wages for all respondents. Further details on the exact survey questions are provided in Appendix A.1.

Hourly Pay The LMS reports pay-related information in annual terms but does not include data on hours worked, for both realized and expected outcomes. We impute annual hours and compute hourly pay using gender-, education-, and industry-specific averages of weekly hours for part-time and full-time workers from CPS monthly data, assuming 50 working weeks per year.[6] This yields an average of 38 hours per week for employed women and 42 for employed men, closely matching CPS counterparts of 37 and 42 hours, respectively. For nonemployed respondents, we impute hours based on full-time averages by gender and education, consistent with the fact that 87% of the unemployed in the CPS search for full-time work. We validate this approach in Appendix A.1, showing that gender gaps in hours, hourly wages, and reservation wages are robust to whether hours are reported, desired, or imputed, and closely match CPS counterparts.

Finally, to reduce the dimensionality of the model estimation while accounting for worker characteristics that are important to explain for empirical wage dispersion, we residualize all pay-related variables—believed wage offers, actual wage offers received, reservation wages, and current wages—by removing the effects of commuting zone, industry interacted with education, and employment or nonemployment duration prior to estimation.

[5]The subjective probability of being unemployed in four months may also reflect expectations of high-frequency transitions within the period—for instance, a worker who loses their job, finds a new one, and loses it again—rather than simply the probability of job separation in four months. However, such transitions are quantitatively negligible: using standard CPS transition rates, the probability of completing a full E-U-E-U cycle within four months is approximately 0.05%, making this concern unlikely to affect our results in any meaningful way.

[6]Appendix A.1 describes in detail how we measure hours worked using CPS data.

Table 1: Gender Differences in Labor Market Beliefs and Realizations

	Men	Women	Difference	
			Unconditional	Conditional
Panel A: Beliefs				
Believed # offers	1.01	1.17	0.16***	0.02
Believed wage offer	10.21	7.20	-3.01***	-2.05***
Panel B: Realizations				
Realized # offers	0.36	0.33	-0.03	-0.07***
Wage offered	4.77	3.34	-1.43***	-1.05***
Panel C: Realization - Belief				
# offers	−0.65	−0.84	-0.19***	-0.09**
Wage offer	−5.44	−3.86	1.58***	1.01***

Notes: Panels A and B report the average of labor market beliefs and realizations separately for men (column 1) and women (column 2). Panel C reports the average difference (realization minus belief). Column 3 reports the unconditional gender differences and Column 4 reports the conditional gender difference controlling for age groups ($< 30, 30 - 44, > 44$), education, race, marital status, presence of children, job search status, and survey date fixed effects. All wages are expressed in hourly terms and are residualized with respect to commuting zone, industry interacted with education, and nonemployment or employment duration, depending on the individual's labor market status. The sample is drawn from the Survey of Consumer Expectations (SCE) over the period November 2015 to November 2019, subject to the selection criteria described in Section 3.1. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

3.2 Evidence for the Model Mechanism

The key novel mechanism in our model is that gender differences in labor market beliefs shape reservation wages and, through them, accepted wages. We provide two pieces of reduced-form evidence in support of this mechanism.

Gender Differences in Beliefs Table 1 documents that both men and women overestimate offer arrival and wages, but with different patterns by gender. Men are more optimistic about wages: they expect the best hourly wage offer to be \$10.21 compared to \$7.20 for women, and overestimate by \$5.44 compared to \$3.86 for women, a difference that remains statistically significant after controlling for demographics. Women, by contrast, overestimate offer arrival by more: they expect 1.17 offers but receive 0.33, compared to 1.01 and 0.36 for men. The unconditional gap in expected offers becomes negligible once we control for observables, suggesting it largely reflects compositional differences. Nonetheless, women remain more overoptimistic than men about offer arrival, as they expect similar numbers of offers to men yet receive fewer.

Reservation Wage Gap According to the model, gender differences in beliefs translate into gender differences in reservation wages, which in turn shape accepted wages. We test this prediction by estimating the gender gap in reservation wages, controlling for observable demographics and labor market beliefs. Column 1 of Table 2 shows that women report reservation wages approximately 23% lower than men, a gap significant at the 1% level and consistent with existing evidence (e.g., Krueger and Mueller, 2016; Barbanchon et al., 2020; Faberman et al., 2025). Column 2 adds beliefs about the number of job offers and the best potential wage offer. This narrows the gender gap to about 8%, accounting for approximately 64% of the original difference. Columns 3 and 4 confirm that this result is not confounded by gender differences in risk aversion.[7] As expected, risk tolerance is positively correlated with the reservation wage (Cortés et al., 2023), but leaves the role of beliefs essentially unchanged. These findings are robust to additional controls for non-wage job amenities, job search intensity, past offers, and industry; to narrower definitions of nonemployment; and to distinguishing between short- and long-term nonemployed individuals, as shown in Appendix Figure A.2. Taken together, these findings highlight the importance of beliefs and their potential role in shaping the gender gap in labor market outcomes through their influence on reservation wages.

4 Model Estimation

Our model features parameters that vary continuously with worker ability a in order to capture unobserved worker heterogeneity that is important to explain empirical wage dispersion, as in Engbom and Moser (2022) or Morchio and Moser (2024). To make estimation tractable, we map ability a to a vector of observable characteristics that matter for wages: age groups (< 30, 30–44, > 44), education (high school or less, some college, college or more), race, marital status, presence of children, and job search status. Prior to estimation, all pay-related variables—believed wage offers, actual wage offers received, reservation wages, and current wages—are residualized by removing the effects of commuting zone, industry interacted with education level, and employment or nonemployment duration, as

[7]We measure risk aversion using two SCE questions: *(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 are measured from 1 not willing at all" to 7 very willing". We include the simple average of the two responses; results are unchanged if we include each measure separately.

Table 2: Labor Market Beliefs and the Reservation Wage Gap

	(1)	(2)	(3)	(4)
Female	-0.233***	-0.084**	-0.215***	-0.075**
	(0.052)	(0.036)	(0.054)	(0.036)
Believed number of offers		0.008		0.007
		(0.012)		(0.011)
Believed wage offer		0.716***		0.714***
		(0.031)		(0.031)
Risk tolerance			0.029	0.016
			(0.018)	(0.011)

Notes: The table reports coefficients from OLS regressions with robust standard errors clustered at the individual level. The dependent variable is the log hourly reservation wage, residualized with respect to commuting zone, industry interacted with education, and employment duration. All regressions control for survey date fixed effects, age, education, race, marital status, presence of children, and job search status. *Risk tolerance* is the simple average of responses to two questions eliciting risk preferences in the SCE, as described in Section 3.1. The sample is restricted to nonemployed respondents drawn from the SCE over the period November 2015 to November 2019, subject to the selection criteria described in Section 3.1. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

described in Section 3.1. This residualization reduces the dimensionality of worker ability while still accounting for key determinants of gender differences in pay, such as industry.[8]

Estimating the extended Burdett–Mortensen model with endogenous vacancy creation, while allowing for worker heterogeneity, nonetheless remains challenging: the equilibrium wage distribution is characterized by a differential equation that must be solved for each worker type. We overcome this by proceeding in three steps. First, we calibrate some parameters to standard values from the literature. Second, we estimate belief parameters alongside true arrival and separation rates and offer distributions by maximum likelihood, exploiting the joint observation of subjective expectations and actual labor market outcomes. In this step, we approximate the observed wage distribution by a log-normal distribution, with all parameters varying flexibly with observable characteristics. Then, we recover the composite productivity distribution and matching efficiency by simulated method of moments, targeting the arrival rates and wage distribution parameters from the second step evaluated at average male characteristics for both genders, so that this step focuses on the residual gender gap rather than the unconditional average. This requires solving the differential equations only twice, once for each gender, holding all other observables fixed.

[8]Following Engbom and Moser (2022), an alternative approach would be to map ability to worker fixed effects from an AKM-style regression, which is not feasible in our setting, given the structure of our data.

We describe each step in turn.

4.1 Preset Parameters

Based on standard values in the literature (Petrongolo and Pissarides, 2001), we set the elasticity of matches with respect to vacancies to $\alpha = 0.5$. We normalize the intercept in the vacancy cost function to $c = 1$, for both genders, since without data on vacancies it is not separately identified from matching efficiency (Equation 7). Finally, we set the mass of firms to $M = 1$ and $\eta = 0.5$, which implies an elasticity of vacancy costs with respect to vacancies of $1 + \eta = 1.5$ (Engbom and Moser, 2022).

4.2 Beliefs and True Labor Market Parameters

Beliefs and true labor market parameters are identified from individual-level variation in the SCE-LMS, which provides joint observation of subjective beliefs and actual labor market realizations for the same workers. We estimate these parameters by maximizing the likelihood of observing the data on beliefs and true wage offers, the number of job offers, and the separation probability. To construct this likelihood, we now describe the mapping between a worker's type a to each of the model parameters and the distributional assumptions for each labor market outcome. Since all parameters are gender-specific, we omit the subscript $g \in \{f, m\}$ to simplify notation.

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

$$\lambda_l^B(a) = \nu_l^B \cdot \exp(\beta_{\lambda_l^B} \cdot a) \qquad \lambda_l(a) = \nu_l \cdot \exp(\beta_{\lambda_l} \cdot a) \tag{20}$$

where $\nu_l^B \sim Gamma\big(k_{\nu_l^B}, \theta_{\nu_l^B}\big)$ and $\nu_l \sim Gamma\big(k_{\nu_l}, \theta_{\nu_l}\big)$, with $l \in \{u, e\}$. This implies that conditional on worker ability a, both the believed and true arrival rates follow a Gamma distribution, $\lambda_l^B|a \sim Gamma\big(k_{\nu_l}^B, \theta_{\nu_l}^B \cdot \exp(\beta_{\lambda_l^B} \cdot a)\big)$ and $\lambda_l|a \sim Gamma\big(k_{\nu_l}, \theta_{\nu_l} \cdot$

$\exp(\beta_{\lambda_l} \cdot a))$, respectively. Therefore, both the expected and received number of offers follow a negative binomial distribution.[9]

Wage offer distributions We assume that, for a worker with ability a, the believed and true wage offer in logs are given by

$$\ln w_a^B = c_{\mu^B} + \beta_{\mu^B} \cdot a + \varepsilon^B \qquad \ln w_a = c_\mu + \beta_\mu \cdot a + \varepsilon \tag{21}$$

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

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

$$\delta_a^B = \phi^B \cdot \exp(\beta_{\delta^B} \cdot a) \qquad \delta_a = \phi \cdot \exp(\beta_\delta \cdot a), \tag{22}$$

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

Current wage Let w_a^c be the current wage of a worker with ability a. In our model, the distribution of wages current, i.e. accepted wages, is characterized by the differential equation in Equation 19, which governs the equilibrium wage distribution as a function of the underlying productivity distribution and labor market parameters. Estimating the model using this distribution directly would require solving the differential equation for every observation in the sample, making estimation computationally challenging. Instead, we approximate the distribution of accepted wages with a log-normal density that depends

[9] Appendix C.2 provides the derivation of these distributions.

on worker ability a and an unobservable error term,

$$\ln w_a^c = c_{\mu^c} + \beta_{\mu^c} a + \varepsilon_c \tag{23}$$

where $\varepsilon_c \sim \ln N(0, \sigma_c)$. Therefore, the observed wage distribution follows a log-normal distribution, $w_a^c \sim \ln N(\mu_a^c, \sigma^c)$, where $\mu_a^c = c_{\mu^c} + \beta_{\mu^c} \cdot a$. Replacing Equation 19 with a log-normal distribution delivers an estimated wage distribution that varies flexibly with worker ability, while remaining tractable. In the third step of the model estimation, we focus on workers at average ability and choose the parameters of the underlying productivity distribution to match the moments of this estimated wage distribution, ensuring consistency across the two steps.

Likelihood The joint observation of subjective beliefs and actual labor market realizations for the same workers in the SCE-LMS yields a tractable likelihood function that exploits the full distributional information in the data to separately identify perceived and true labor market parameters. Appendix C.1 derives the likelihood function in detail.

Maximizing Equation C.3 delivers estimates of three sets of parameters, all estimated separately for men and women. First, the coefficients governing how worker ability a maps to believed and true job arrival rates $\left(\beta_{\lambda_l^B}, \beta_{\lambda_l}\right.$, where $l \in \{u, e\}$, in Equation 20$\left.\right)$, believed and true separation rates $\left(\beta_{\delta^B}, \beta_\delta\right.$ in Equation 22$\left.\right)$, the mean of the believed and true wage offer distributions $\left(c_{\mu^B}, \beta_{\mu^B}, c_\mu, \beta_\mu\right.$ in Equation 21$\left.\right)$, and the mean of the observed wage distribution $(c_{\mu^c}, \beta_{\mu^c}$ in Equation 23). Second, the parameters governing the dispersion of the error terms $\left(k_{\nu_l^B}, \theta_{\nu_l^B}, k_{\nu_l}, \theta_{\nu_l}, \sigma^B, \sigma, \sigma^c, k_{\phi^B}, \theta_{\phi^B}, k_\phi, \theta_\phi\right.$, where $\left.l \in \{u, e\}\right)$. Finally, from the estimated parameters, we can recover the flow value of nonemployment and relative search intensity. In particular, the flow value of nonemployment for each worker type is recovered as the residual between the observed reservation wage and the reservation wage predicted by the model, using Equation 3. Since we run the estimation separately for men and women, they are specific to both gender and ability a. Columns 1 to 8 of Table C.1 and Table C.2 in Appendix C.4 report the estimated parameters for women and men, respectively.

4.3 Firm Productivity and Matching Efficiency

Having obtained estimates of beliefs and true labor market parameters in the previous step, we now estimate the remaining parameters, namely the ones governing the composite productivity distribution and matching efficiency, by simulated method of moments. We proceed as follows. We begin by evaluating belief and true arrival and separation rates as well as belief offer distribution at the mean observable characteristics of men $\bar{a}_m$ for both genders.[10] Formally, let y^B and y denote the believed and true counterparts of a model parameter, and let $\hat{\Omega}^g_{y^B}$ and $\hat{\Omega}^g_y$ denote the sets of estimated coefficients governing y^B and y for gender g. We compute gender-specific parameters as

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

By holding observables fixed at $\bar{a}_m$ for both genders, we ensure that differences in the model parameters, both beliefs and their true counterpart, across genders are not confounded by compositional differences between men and women in the sample. This also implies that the system of differential equations in Equation 19 needs only to be solved twice, for two otherwise identical workers who differ solely in gender, yielding a substantial reduction in computational burden.

Given the belief parameters $(\lambda^B_u, \lambda^B_e, \delta^B, F^B(w))$, we obtain the reservation wage R_g for each gender g together with Equation 3. Relative search intensity s follows from the ratio of arrival rates while employed to those while unemployed, as implied by Equation 13, yielding $s_m = 2.49$ and $s_f = 2.16$. From Equation 10 and Equation 5, we recover μ using the estimated nonemployment rates ($u_m = 0.22$ and $u_f = 0.27$).[11] Finally, we set the *true* separation rate δ_g equal to its estimated value in the prior step.

[10] Recall that ability is mapped into a vector of observable characteristics: age groups (young, prime-age, old), education (high school or less, some college, college or more), race (white, non-white), marital status, presence of children, and job search status. Accordingly, $\bar{a}_m$ corresponds to the share of men in each category— that is, the average observable characteristics of men in our sample.

[11] In particular, we obtain $\mu_m/(V_m\chi^2_m) = 23.12$ and $\mu_f/(V_f\chi^2_f) = 30.67$. In estimation, we solve for V such that $\lim_{p\to\bar{p}} h(p) = 1$ for both men and women. Given the vacancy rates satisfying the CDF restriction of the wage distribution and estimated matching efficiency, we back out a relative measure of workers to firms, μ.

We assume firm composite productivity $\tilde{p}$ is log-t distributed with pdf:

$$\gamma(\tilde{p};\mu^g_{\tilde{p}},\sigma^g_{\tilde{p}},\nu^g_{\tilde{p}})\frac{\Gamma\left(\frac{\nu^g_{\tilde{p}}+1}{2}\right)}{\sqrt{\nu^g_{\tilde{p}}\pi}\,\sigma^g_{\tilde{p}}\,\tilde{p}\,\Gamma\left(\frac{\nu^g_{\tilde{p}}}{2}\right)}\left(1+\frac{(\log\tilde{p}-\mu^g_{\tilde{p}})^2}{\nu^g_{\tilde{p}}(\sigma^g_{\tilde{p}})^2}\right)^{-\frac{\nu^g_{\tilde{p}}+1}{2}}. \tag{24}$$

where $\mu^g_{\tilde{p}}$, $\sigma^g_{\tilde{p}}$, and $\nu^g_{\tilde{p}}$ are gender-specific location, scale, and degrees-of-freedom parameters. The parameter $\nu^g_{\tilde{p}}$ governs tail thickness, with smaller values implying heavier tails and greater dispersion. This flexibility is important because on-the-job search causes workers to sort toward higher composite productivity firms, compressing the equilibrium wage distribution $G(w)$ (Equation 4) relative to the underlying offer distribution $F(w)$ (Equation 18). Since the offer distribution is itself a transformation of the composite productivity distribution, heavier tails help offset this compression and allow the model to match the empirical wage distribution.

The parameters to be estimated by simulated methods of moments are therefore $\{\mu^m_{\tilde{p}},\sigma^m_{\tilde{p}},\nu^m_{\tilde{p}},\chi_m\}$ for men and $\{\mu^f_{\tilde{p}},\sigma^f_{\tilde{p}},\nu^f_{\tilde{p}},\chi_f\}$ for women. We choose these parameters, to match the first, second, and third uncentered moments of the wage distribution and the arrival rates obtained in the previous step, evaluated at the mean male observables in our sample. Table 3 reports the model parameters. Expected log productivity is 4.81 for men and 4.53 for women, implying that firms offering jobs to men are, on average, about 6% more productive than those offering jobs to women, conditional on observable worker characteristics.[12] While we do not take a stand on the sources of the implied lower productivity for women, it is consistent with evidence that firms hiring women tend to pay lower wage premiums (Card et al., 2016), as well as with taste-based discrimination (Becker, 1971; Flabbi, 2010), and gender-specific preferences for job attributes (Rosen, 1986; Goldin, 2014; Morchio and Moser, 2024; Faberman et al., 2025). Matching efficiency is similar across genders and close to one for both.

Table 3: Model Parameters

	Men	Women
Panel A: Preset Parameters		
Measure of Firms (M)	1.0	1.0
Matching Function Elasticity (α)	0.5	0.5
Vacancy Posting cost (c)	1.0	1.0
Elasticity of Vacancy Posting Cost (η)	0.5	0.5
Panel B: Recovered from MLE		
Believed Arrival Rate, Nonemployed (λ_u^B)	1.161	1.009
Believed Arrival Rate, Employed (λ_e^B)	1.129	1.061
Believed Separation Rate (δ^B)	0.148	0.148
Mean of Believed Offer distribution (μ^B)	1.894	1.681
SD of Believed Offer distribution (σ^B)	0.565	0.562
Separation Rates (δ)	0.040	0.048
Flow Value of Nonemployment (b)	4.293	4.495
Relative Search Efficiency (s)	2.489	2.159
Measure of Workers ($\mu_m/(V_m \chi_m^{1/0.5})$	23.121	30.675
Panel C: SMM Parameters		
Location parameter ($\mu_{\tilde{p}}$)	0.435	0.453
Scale parameter ($\sigma_{\tilde{p}}$)	0.191	0.155
Dispersion parameter (ν)	28.805	25.105
Match Efficiency (χ)	1.000	1.000

Notes: Panel A reports parameters preset to standard values from the literature. Panel B reports parameters recovered from the maximum likelihood estimation, evaluated at the mean male characteristics $\bar{a}_m$ for both genders. Panel C reports parameters estimated by simulated method of moments, targeting the first three uncentered moments of the wage distribution and the arrival rates for both genders. Firm productivity follows a log-t distribution with location parameter $\mu_{\tilde{p}}$, scale parameter $\sigma_{\tilde{p}}$, and degrees-of-freedom parameter $\nu_{\tilde{p}}$.

4.4 Model Fit

We assess the fit of the model along several dimensions. Table 4 reports model and data moments for the key variables used in the maximum likelihood estimation. Overall, the model aligns well with the data. It matches gender differences in the reservation wage and predicts a women-to-men wage ratio of 0.68, capturing nearly 100% of the ratio observed in the data. Although the model underestimates expectations about the number of job offers, it matches the actual number of offers received and the believed and true wage offer distributions well. Appendix Figure D.1 further shows that the model replicates the gender gaps in beliefs, realizations, and bias for both the number of offers and wage offers, as

[12] Both productivity distributions are close to log-normal, however women's productivity has slightly heavier tails. As $\nu \to \infty$ the productivity distribution approaches log-normal, however $\nu \geq 30$ is often considered approximately log-normal.

Table 4: Model Fit: Maximum Likelihood

	Men		Women	
	Data	Model	Data	Model
Panel A: Beliefs				
Believed # offers	1.01	0.91	1.17	1.01
nonemployed	1.25	1.14	1.51	1.30
employed	0.96	0.85	1.07	0.90
Believed wage offer	10.21	9.86	7.20	6.85
Panel B: Realizations				
Realized # offers	0.36	0.34	0.33	0.32
unemployed	0.15	0.16	0.22	0.23
employed	0.42	0.38	0.37	0.35
Wage offered	4.77	4.66	3.34	3.40
Panel C: Bias				
# offers	-0.65	-0.57	-0.84	-0.69
unemployed	-1.10	-0.98	-1.29	-1.07
employed	-0.55	-0.46	-0.70	-0.55
Wage offer	-5.44	-5.20	-3.86	-3.45
Panel D: Outcomes				
Reservation wage	5.25	5.15	3.77	3.76
Accepted wage	14.50	14.50	9.87	9.90
Employment duration	99.75	90.21	79.98	75.90

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

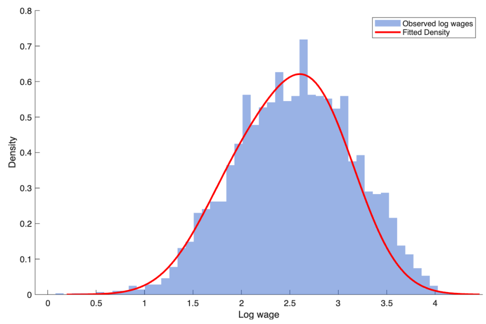
well as the gender gaps in reservation wages, accepted wages, employment duration, and labor market transition rates, with model estimates falling within the confidence intervals of their data counterparts throughout. Finally, Panels (a) and (b) of Figure 1 show that the estimated log-normal distribution captures the mean and dispersion of log-wages for men and women well.

Table 5 reports the moments targeted in the simulated method of moments estimation. The model matches the first three uncentered moments of the wage distribution and the arrival rates for both men and women. Panels (c) and (d) of Figure 1 plot the estimated CDF of wages from the maximum likelihood estimation against the CDF of the equilibrium wage distribution produced by Equation 19. The two CDFs are nearly identical for both men and women, showing that the model successfully replicates the full distribution of wages.

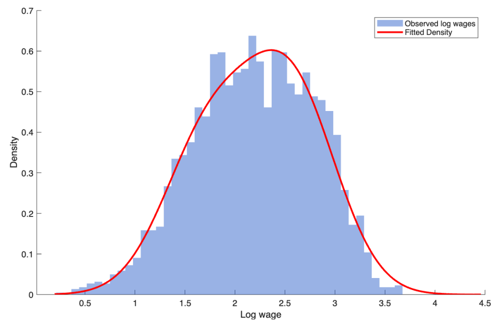
Figure 1: Model Fit: Wage Distribution

Panel A: Maximum Likelihood

(a) Men

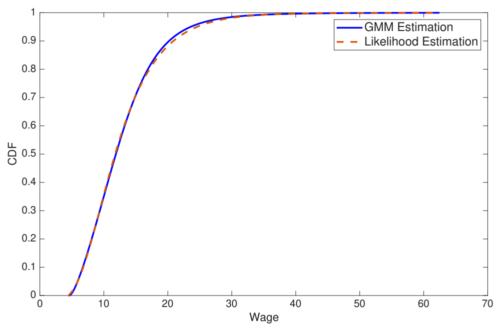


(b) Women

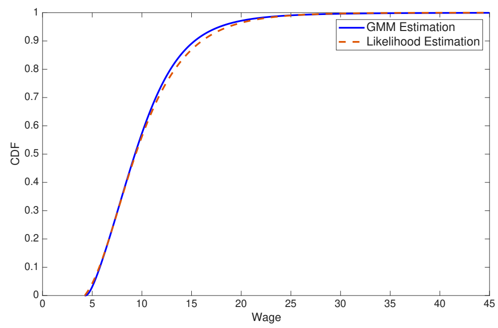


Panel B: Simulated Method of Moments

(c) Men



(d) Women



Notes: Panel A plots the empirical distribution of log-wages against the log-normal density estimated in the first stage for men and women separately. Panel B plots the cumulative distribution of wages from the first-stage log-normal estimates (dashed line) against the equilibrium wage distribution produced by the second-stage simulated method of moments estimation (solid line), evaluated at mean male characteristics.

Beyond these moments, Appendix Figure D.2 shows that the model replicates the relationship between reservation wages and both the believed number of offers and the believed wage offer. Appendix Figure D.3 shows that model-predicted OLS coefficients from regressions of reservation wages and wages on observable worker characteristics fall within the confidence intervals of their data counterparts.

5 Counterfactual Analysis

In this section, we use the estimated model to decompose the gender wage gap into contributions from beliefs and true labor market parameters, and to evaluate the implications of

Table 5: Model Fit: Simulated Method of Moments

	Men		Women	
	Data	Model	Data	Model
$E[w]$	12.90	12.96	10.08	10.14
$E[w^2]$	204.15	203.40	121.88	121.27
$E[w^3]$	3959.71	3963.69	1768.05	1770.45
λ_u	0.141	0.141	0.133	0.133
λ_e	0.352	0.352	0.286	0.286

Notes: The table reports the moments targeted in the simulated method of moments estimation, evaluated at mean male characteristics. $E[w]$, $E[w^2]$, and $E[w^3]$ are the first three uncentered moments of the wage distribution. λ_u and λ_e are the job arrival rates for nonemployed and employed workers, respectively.

two policy-relevant counterfactuals for gender differences in wages and lifetime earnings.

5.1 Decomposition of the Gender Wage Gap

The estimated model implies a conditional gender wage gap of 24.4%. We can decompose this gap into three components by sequentially equalizing women's parameters to those of men: (i) beliefs about labor market parameters $(\lambda_u^B, \lambda_e^B, \delta^B, F^B(w))$, labor market parameters $(\mu_{\tilde{p}}, \sigma_{\tilde{p}}, \nu_{\tilde{p}}, \delta, s, \chi)$ and the flow value of nonemployment b. Each counterfactual is cumulative, so that in the final step all parameters for women are equal to those of men. Table 6 summarizes the decomposition results.

Assigning women the belief parameters of men reduces the gender wage gap by 6.1 percentage points, implying that gender differences in beliefs account for approximately 25% of the model-implied wage gap (column 2, Table 6).[13] As women believe they face a less favorable wage offer distribution relative to men, they perceive their outside option to be less attractive than they would under men's beliefs, leading them to set lower reservation wages and accept worse jobs. Assigning women the belief parameters of men corrects this, raising their reservation wages and shifting them toward better-paying jobs.

We next equalize labor market parameters, namely the composite productivity distribution $(\mu_{\tilde{p}}, \sigma_{\tilde{p}}, \nu_{\tilde{p}})$, separation rate δ, search intensity s, and matching efficiency χ, to men's values. These parameters determine women's wages through two channels: the wage offer distribution available to them and the speed at which they climb the job ladder. The model

[13] Specifically, we evaluate women's believed arrival rates, separation rate, and wage offer distribution using the estimated coefficients for men, holding all other parameters and the flow value of nonemployment fixed.

Table 6: Decomposition of the Gender Wage Gap

	Model	Belief Parameters	Labor Market Parameters	Nonemployment Value
Wage Gap	24.38	18.30	-3.18	0.00
Change		6.08	21.48	-3.18
% explained		24.93	88.11	-13.04

Notes: Table reports a decomposition of the model-implied gender wage gap. Column 1 displays the conditional gender gap implied by the model at mean male characteristics $\bar{a}_m$ and equating the measure of such types across genders, that is, equating μ. Column (2) removes differences in beliefs, and column (3) removes differences in labor market parameters. Column (4) equalizes flow values of unemployment between genders. The model counterfactuals are *cumulative* such that in the last column, all model parameters for women are the same as for men. The wage gap is defined as $100 \cdot (1 - w_f / w_m)$, where w_f and w_m represent average wages of women and men, respectively. *Change* is the percent point change in the wage gap, and *% Explained* the proportion of the wage gap explained by each channel.

estimates imply that women face less favorable composite productivity distributions and are more likely to fall off the job ladder than men (Table 3 and Table 5). Equalizing all labor market parameters reduces the gender wage gap by 21.5 percentage points, accounting for approximately 88% of the model-implied gap (Column 3, Table 6). Finally, women have a higher flow value of nonemployment than men, so equalizing this parameter to men's values lowers women's reservation wages, slightly widening the gender gap.

5.2 Policy Counterfactuals

We now use the estimated model to conduct two policy-relevant counterfactuals. First, we simulate an information intervention by making beliefs unbiased for men and women. An example of such a policy is pay transparency legislation, where firms are required to disclose information on pay, potentially reducing biased beliefs. Second, given biased beliefs, we investigate the impact of equalizing women's true labor market parameters to those of men. We interpret this counterfactual as policies aimed at firms, such as equal pay mandates or gender quotas. For each counterfactual, we compute average wages and lifetime earnings for men and women, focusing on the residual wage gap, which captures gender differences after accounting for differences in observables (Column 1 in Table 6). Results are summarized in Table 7 and Table 8.

Average Wage We compute the reservation wage for both genders at the average male ability $\bar{a}_m$, $R_g(\bar{a}_m)$, using Equation 3 and the parameter values of the model reported in Table 3. Combining $R_g(\bar{a}_m)$ with Equation 19, we obtain the predicted average wage for men and women.

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

$$\Lambda = \frac{W_f}{W_m} - 1 \tag{25}$$

where W_m and W_f are the discounted sum of consumption for the average men and women, that is, $W_g = U(R_g(\bar{a}_m))/r$, where

$$U(R_g(\bar{a}_m)) = \frac{1}{r + \lambda_u(g,a)(1 - F(R_g(\bar{a}_m|g,a)))} \Big[b(g,a) + \lambda_u(g,a)(1 - F(R_g(\bar{a}_m|g,a)))R_g(\bar{a}_m) \tag{26}$$

$$+ \lambda_u(g,a)\left(1 + \lambda_e(g,a)(1 - F(R_g(\bar{a}_m|g,a)))\right) \int_{R_g(\bar{a}_m)}^{\bar{p}_{ga}} \frac{1 - F(w|g,a)}{r + \delta_{ga} + \lambda_e(g,a)(1 - F(w|g,a))} dw \Big]$$

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

5.2.1 Corrected Beliefs

Our first counterfactual removes belief bias for both women and men by recalculating reservation wages (Equation 3) using *actual* labor market parameters instead of beliefs. Unlike the decomposition exercise, which asks how the wage gap changes if women share men's beliefs, this counterfactual asks how the wage gap would change if both men and women held unbiased beliefs.

Column 2 of Table 7 shows that under unbiased beliefs, both men's and women's wages decrease, but the reduction is smaller for women, narrowing the wage gap by 16 percentage points. As workers recognize their outside option to be worse than they believed, reservation

Table 7: Counterfactual: Corrected Beliefs

	Baseline	All	Arrival Rates	Offer Distribution	Separation Rate
Wage					
Gap	24.38	7.63	27.40	22.60	25.68
Women (% Δ)		-13.57	-51.55	1.45	-0.90
Men (% Δ)		-29.24	-49.54	-0.88	0.83
Lifetime Earnings					
Gap	1.62	-7.97	-3.46	1.13	2.90
Women (% Δ)		-5.84	-15.22	-0.02	-0.94
Men (% Δ)		-14.20	-19.38	-0.51	0.36

Notes: The table reports results from a counterfactual scenario in which we correct beliefs about labor market parameters for both men and women. Column 1 reports the baseline gender gaps in wages and lifetime earnings. The remaining columns report results under unbiased beliefs, correcting all beliefs simultaneously (All) or separately for arrival rates, the offer distribution, and the separation rate. The wage gender gap is defined as $100 \cdot (1 - w_f/w_m)$, and the lifetime earnings gap is $100 \cdot (-\Lambda)$, where Λ is given by Equation 25. % Δ denotes the percentage change in wages or lifetime earnings relative to the baseline.

wages decrease, and firms respond by lowering their offer distributions. As a result, lifetime earnings decrease for both genders. The decrease is larger for men, whose beliefs are more biased initially, reversing the gender gap in lifetime earnings.

Columns 3–5 show the effects of correcting beliefs separately for arrival rates, the wage offer distribution, and the separation rate. Correcting only arrival rate beliefs lowers wages for both genders but more so for women, widening the wage gap, as firms respond by lowering wages while increasing vacancies. As a result, all workers are worse off in terms of lifetime earnings, but men experience a larger decrease, and the gap in gender lifetime earnings reverses. Correcting only beliefs about the wage offer distribution, mimicking a pay transparency policy, has a small effect, reducing the wage gap by about 1.8 percentage points, consistent with recent empirical evidence (Gulyas et al., 2021; Duchini et al., 2022; Bennedsen et al., 2022). Taken together, these results show that correcting workers' beliefs narrows the wage gap but has the unintended consequence of reducing lifetime earnings for both men and women, with men experiencing larger losses that reverse the gender gap in lifetime earnings.

5.2.2 Equalized Labor Market Parameters

Our second counterfactual eliminates gender differences in labor market parameters, namely differences in search parameters (s and χ), the composite productivity distribution ($\mu_{\tilde{p}}$, $\sigma_{\tilde{p}}$, $\nu_{\tilde{p}}$), and the separation rate δ, while keeping women's beliefs unchanged. Table 8 shows that eliminating gender differences across all labor market parameters increases women's wages by 27%, reducing the conditional wage gap to 3.6%. It also raises women's lifetime earnings by 3%, reversing the gap. The key driver is the composite productivity distribution: equalizing it alone increases women's wages by 15.6%, reduces the wage gap by 12 percentage points, and closes the lifetime earnings gap (Column 4). By contrast, equalizing search parameters reduces the wage gap by only 2 percentage points, and equalizing separation rates reduces it by nearly 6 percentage points, as women become less likely to fall off the job ladder.

The estimated gender difference in the composite productivity distribution absorbs different underlying mechanisms that generate gender wage disparities, including differences in firm productivity (Card et al., 2016), taste-based discrimination (Becker, 1971; Flabbi, 2010), and gender-specific preferences for non-wage attributes (Goldin, 2014; Morchio and Moser, 2024; Faberman et al., 2025). While separately identifying these forces is beyond the scope of this paper, our findings suggest that tackling the mechanisms that sort women into lower-paying firms are more effective at reducing gender inequality in pay than policies focused on providing wage information. Moreover, it raises lifetime earnings for women, whereas correcting beliefs only partially narrows the wage gap while reducing lifetime earnings for both men and women.

5.3 Robustness: Risk Aversion

Given the well-documented gender differences in attitudes toward financial risk (Eckel and Grossman, 2002; Charness and Gneezy, 2012), we relax the assumption of risk neutrality. Specifically, we assume that the instantaneous utility function of workers is given by $u(y) = \frac{y^{1-\rho_g}-1}{1-\rho_g}$, where ρ_g is the coefficient of relative risk aversion, allowed to differ by gender, $g \in \{f, m\}$. Risk aversion generally dampens the impact of expectation biases. This is because risk-averse makes workers less responsive, in terms of reservation wages,

Table 8: Counterfactual: Equalized Labor Market Parameters

	Baseline	All	Search Parameters	Firm Productivity	Separation Rate
Wage					
Gap	24.38	3.65	22.31	12.57	19.31
Women (% Δ)		27.42	2.74	15.62	6.71
Lifetime Earnings					
Gap	1.62	-1.68	1.78	-0.30	1.21
Women (% Δ)		3.35	-0.17	1.95	0.41

Notes: The table reports results from a counterfactual scenario in which we equalize labor market parameters by giving women the same values as men, while keeping women's beliefs unchanged. Column 1 reports the baseline gender gaps in wages and lifetime earnings. The remaining columns report results equalizing all parameters simultaneously (All) or separately for search parametera (s and χ), the composite productivity distribution ($\mu_{\tilde{p}}, \sigma_{\tilde{p}}$), and the separation rate δ. The wage gender gap is defined as $100 \cdot (1 - w_f/w_m)$, and the lifetime earnings gap is $100 \cdot (-\Lambda)$, where Λ is given by Equation 25. % Δ denotes the percentage change in wages or lifetime earnings relative to the baseline.

to changes in beliefs and labor market parameters. Using gender-specific values of ρ_g from Cortés et al. (2023), the contribution of beliefs to the gender wage gap decreases to 18%, remaining substantial, while differences in risk aversion themselves account for only 1%. The main findings from the counterfactual analysis remain robust: equalizing labor market parameters continues to play a substantially larger role in closing the gender wage gap than correcting beliefs for both men and women (see Appendix E for details).

6 Conclusion

This paper investigates the role of labor market beliefs in shaping the gender pay gap. To do so, we embed subjective expectations into the extended version of Burdett and Mortensen (1998) with endogenous job creation by Morchio and Moser (2024). In the model, individual beliefs affect wages through their impact on reservation wages. Using the Survey of Consumer Expectations, we provide evidence supporting this mechanism.

Our analysis shows that gender differences in beliefs about labor market parameters account for approximately 25% of the gender wage gap. Our counterfactual analysis reveals an important asymmetry. Correcting beliefs narrows the wage gap but triggers an unintended general equilibrium response: as reservation wages fall, firms post lower wages, reducing lifetime earnings for both men and women. Instead, removing the underlying gender differences in the labor market closes far more of the wage gap and raises lifetime earnings for women.

These findings contribute to the ongoing debate about the causes of the gender pay gap and the policies that can close it. Addressing structural barriers that sort women into lower-paying firms, whether stemming from firm pay premiums, taste-based discrimination, or gender-specific preferences for non-wage amenities, is not only more effective at closing the gender wage gap than correcting beliefs, but also avoids the unintended cost of leaving both men and women worse off.

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A Data Appendix

A.1 Sample Construction and Variable Definitions

Sample The sample draws from the SCE, a monthly rotating panel of approximately 1,300 US household heads, each participating for up to 12 months. Active panel members are eligible for the Labor Market Survey (LMS), which collects information on job search behavior, labor market beliefs, reservation wages, and realized outcomes. We use data from November 2015 to November 2019, restricting to individuals aged 20–65 with non-missing information on education, race, marital status, children, reservation wage, and perceived job offer probability, and dropping observations with wages below $4/h. This yields a final sample of 7976 observations from 4197 unique individuals.

Table A.1 describes the main characteristics of our sample. Individuals are, on average, 45.4 years old, around 80% are white, and almost 43% have a college degree. Men make up slightly more than half of the sample. Table A.2 shows that the sample aligns well with the demographic characteristics of household heads in the Current Population Survey (CPS) over the same period.

Table A.1: Descriptive Statistics

	Full	Men	Women	p-value
Age (years)	45.4	46.3	44.3	0.000
White	80.4	83.5	77.1	0.000
College Degree or More	42.6	47.6	37.1	0.000
Children (total)	.88	.86	.9	.1767
Married /Partner	66.8	72.5	60.7	0.000
# observations	7976	4209	3767	
# respondents	4197	2171	2026	

Notes: The table reports means for all respondents in our sample and separately by gender. The sample is a sub-sample from SCE subject to the criteria described in the main text from November 2015 to November 2019.

One potential concern is that women who are household heads differ systematically from other women, particularly in the labor market. Table A.3 and Table A.4 show this is not the case: although women household heads differ slightly from other women in demographic characteristics, the two groups look very similar along labor market dimensions, including employment rates, hours worked, and occupation distribution.

Table A.2: Descriptive Statistics: SCE - Labour Market Supplement vs CPS

Variable (mean)	SCE - LMS	CPS	p-value
Age (years)	45.4	44.3	0.880
Female	47.7	48.3	0.983
White	80.4	76.5	0.864
College Degree or More	42.6	36.4	0.810
Children (total)	0.88	0.87	0.987
Married/Partner	66.8	58.5	0.754

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

Table A.3: Descriptive Statistics: Women HH vs Women non-HH and MaMenles

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

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

Hours Imputation The LMS reports pay-related variables in annual terms and does not record hours worked. We impute annual hours using gender-, education-, and industry-specific averages from CPS monthly data, assuming 50 working weeks per year. Specifically, we use the CPS variable `uhrswork1`, which records usual weekly hours at the main job, and define part-time as fewer than 35 hours and full-time as 35 or more. For employed respondents, we assign hours based on full-time and part-time averages disaggregated by

Table A.4: Occupation Shares
(% of employed)

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

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

gender, education, and industry.[14] For nonemployed respondents, we assign full-time hours by gender and education, consistent with CPS evidence that 87% of the unemployed search for full-time work. Reservation wages and earnings expectations reported by part-time workers are assumed to correspond to part-time work; those reported by full-time and nonemployed workers are assumed to reflect full-time work. Results are robust to the alternative imputation of Conlon et al. (2018), which assumes 40 hours for full-time and 20 hours for part-time workers for 52 weeks per year.

We validate this approach using the Job Search Survey (JSS), another supplement to the SCE first administered in October 2013 and fielded each October since. Because both supplements draw respondents from the monthly SCE, the samples are comparable and individuals can be matched across supplements. Crucially, the JSS collects both hours worked and preferred hours worked, making it well-suited for validating our imputation. We further validate the approach using CPS data restricted to household heads aged 20–65 to ensure comparability with the SCE sample.[15]

Table A.5 reports the raw gender gaps, defined as the coefficient on a female dummy in an OLS regression, across reported, imputed and desired hours, as well as four hourly pay outcomes. Three findings stand out. First, the gender gap in hours is consistently around four hours per week regardless of whether we use reported, imputed, or preferred hours in the JSS, and closely matches the gap observed in the CPS. Second, the raw gender wage gap is nearly identical whether constructed from reported or imputed hours in the

[14] We consider four education levels: less than high school, some college, a bachelor's degree, and more than a bachelor's degree.

[15] A more detailed description of the JSS survey is in Faberman et al. (2022).

JSS, mirrors the gap in the LMS, and aligns closely with the CPS. Third, the gender gap in reservation wages is very similar across the different methods to measure hours and data sources. The gender gap in expected wage offers, measured only in the LMS, is similarly robust to whether we use imputed or preferred hours. Taken together, these results support the validity of our imputation procedure.

Table A.5: Robustness of Gender Gaps to Hours Measurement

	Job Search Survey			Labour Market Survey		CPS
	Reported	Imputed	Desired	Imputed	Desired	
Hours	-4.01***	-4.00***	-4.69***			-4.34***
	(0.69)	(0.30)	(0.59)			(0.02)
Wage	-11.15***	-11.15***		-11.29***		-12.17***
	(0.88)	(0.88)		(0.51)		(0.16)
Reservation Wage	-9.67***	-9.67***	-10.63***	-10.98***	-10.62***	
	(0.77)	(0.77)	(0.86)	(0.48)	(1.35)	
Expected Best Offer				-11.93***	-11.64***	
				(0.70)	(1.30)	
Expected Average Offer				-10.40***	-9.97***	
				(0.63)	(1.16)	

Notes: Table reports the coefficient on the female dummy from OLS regressions of each variable on a female indicator. All pay-related variables are measured as hourly amounts in dollars. *Reported* corresponds to hours worked as reported in the Job Search Survey (JSS). *Imputed* corresponds to hours imputed based on CPS averages by gender, education, and industry, as described in Section 3. *Desired* corresponds to preferred hours of work as reported in the JSS. The last column reports the gender gap estimated using data from CPS (2015–2019), restricted to household heads aged 20–6 5to ensure comparability with the SCE sample. Standard errors in parentheses. ***, ** and * represent statistical significance at the 1%, 5% and 10% levels, respectively.

Survey Questions The LMS asks all respondents, regardless of their current employment status: *What do you think is the percent chance that within the coming four months, you will receive at least one job offer?*".[16] If respondents report a non-zero probability, they are subsequently asked more detailed questions about their expectations regarding job offers and potential salaries. Specifically, the survey asks:

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

[16]For employed respondents, the question asks specifically about offers from *another employer*.

W e use these questions to measure the expected number of job offers and expected wages, respectively. The survey also collects information on offers actually received, regardless of acceptance:

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

We use the first question to measure realized number of job offers and the second question to realized wage offered. Reservation wages are elicited by asking:

- "*Suppose someone offered you a job today in a line of work that you would consider. What is the lowest wage or salary you would accept (BEFORE taxes and other deductions) for this job?*"

Finally, to measure beliefs about separation risk, we use two questions asked to employed respondents.

- *What do you think is the percent chance that four months from now you will be... i) Unemployed and looking for work; (ii) Unemployed and NOT looking for work.*

We sum the two reported probabilities to obtain the subjective separation probability, thereby capturing both transitions to unemployment and exits from the labor force.[17]

[17]We note that this measure asks about the probability of being unemployed at the four-month horizon rather than the probability of losing one's job, which are conceptually distinct, as it also captures the possibility of high-frequency employment transitions within the four-month window However, this distinction is unlikely to materially affect our results. Using standard monthly transition rates from Shimer (2012) — a monthly E-U rate of 3.5% and a monthly U-E rate of 42.5% — the probability going to unemployment, find a job and then lose it within four months is approximately $0.035 \times 0.425 \times 0.035 \approx 0.0005$, or 0.05%.Given that the average subjective separation probability in the SCE is approximately 3%, such high-frequency transitions account for at most 1.7% of the total reported probability ($0.0005/0.03 \approx 0.017$), implying that the subjective probability mostly reflects transitions involving losing the current job and remaining nonemployed at the four-month horizon.

A.2 Additional Empirical Results

Table A.6: Expectations and Job Search Effort

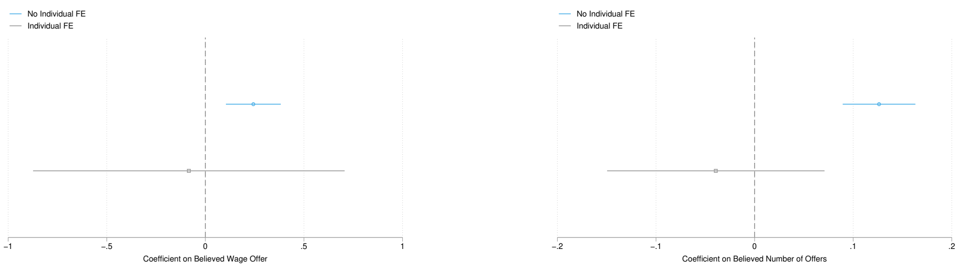
	(1)	(2)	(3)	(4)	(5)
female	2.521	1.884	2.575	1.946	2.474
	(3.068)	(2.631)	(3.168)	(2.752)	(3.260)
exp. best offer		-2.402		-2.375	15.176
		(2.275)		(2.329)	(15.229)
exp. # offers			9.659	9.658	61.131
			(9.364)	(9.366)	(59.443)
Observations	1268	1268	1268	1268	1268

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

Figure A.1: Private Information in Labor Market Beliefs

(a) Wage Offer Received at t

(b) Number of Offers Received at t

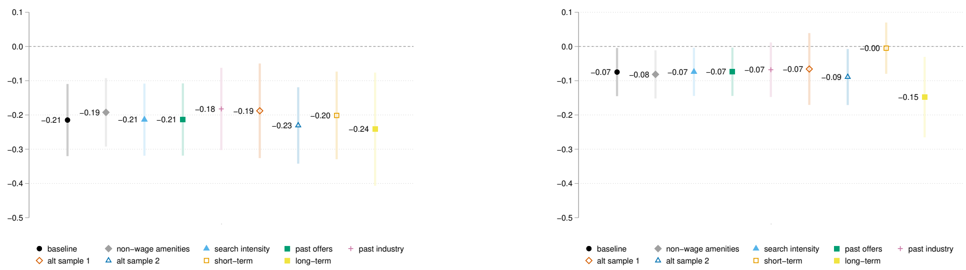


Notes: Each panel plots the coefficient on lagged beliefs from an OLS regression of realized outcomes on their lagged believed counterparts, controlling for lagged realizations. Panel (a) reports the coefficient on the lagged believed wage offer (in logs) from a regression of the realized best wage offer (in logs). Panel (b) reports the coefficient on the lagged believed number of offers from a regression of the realized number of offers. Both specifications are estimated with and without individual fixed effects. Capped spikes represent 95% confidence intervals. The sample is drawn from the Survey of Consumer Expectations (SCE) over the period November 2015 to November 2019, subject to the selection criteria described in Section 3.1.

Figure A.2: Reservation Wage Gap: Robustness Checks

(a) Not controlling for expectations

(b) Controlling for expectations



Notes: Panel (a) and (b) replicate, respectively, columns 3 and 4 in Table 2 under different specifications: *non-wage amenities* includes a set of categorical variables that equal 1 if the employer provides the following benefits: (i) traditional pension plans, (ii) contribution to a retirement account, (iii) health insurance, (iv) dental or vision insurance, (v) housing or housing subsidy, (vi) life or disability insurance, (vii) commuter benefits and (viii) childcare assistance; *search intensity* controls for how many hours individuals search for a job in the past 7 days; *past offers* controls for the number of offers receive in past 4 months; *past industry* includes previous job's industry fixed effects; *alt sample 1* uses CPS-definition of job seekers without a job; *alt sample 2* focus on non-employed reporting a positive likelihood of working within 4 months; *short-* and *long-term* use a sample of short-term ($\leq$2 years) and long-term (>2 years) non-employed individuals, respectively. Capped spikes represent 95% confidence intervals. The sample is drawn from the Survey of Consumer Expectations (SCE) over the period November 2015 to November 2019, subject to the selection criteria described in Section 3.1.

B Model Appendix

B.1 The employment distribution

The measure of workers of type (g, a) below a certain wage w must be constant in the steady state equilibrium. Let $G(w \mid g, a)$ denote the cumulative distribution of observed wages. This is determined in steady state by the following flow-balance equation,

$$\lambda^U(g,a)F(w \mid g,a)u_{ga} = [\delta(g,a) + \lambda^E(g,a)[1 - F(w \mid g,a)]]G(w \mid g,a)(1 - u_{ga}), \tag{B.1}$$

where the left-hand side is the inflow into the stock of workers employed below wage w, and the right-hand side is the outflow from the stock of workers employed below wage w. Therefore,

$$G(w \mid g,a) = \frac{\lambda^U(g,a)F(w \mid g,a)}{\delta(g,a) + \lambda^E(g,a)[1 - F(w \mid g,a)]} \cdot \frac{u_{ga}}{1 - u_{ga}} \tag{B.2}$$

B.2 Model Equilibrium

In an equilibrium, firms choose wages and vacancies to maximize profits, Equation 8. Assuming a vacancy posting cost function $c^v(v_{ga}) = c\frac{v_{ga}^{1+\eta}}{1+\eta}$, the first order condition for wages and vacancies are:

$$cv_{ga}^{\eta} = (pa - w_{ga} - z_{ga})\frac{\partial l_{ga}(w,v)}{\partial v} \tag{B.3}$$

$$l_{ga}(w,v) = (pa - w_{ga} - z_{ga})\frac{\partial l_{ga}(w,v)}{\partial w} \tag{B.4}$$

The derivatives of labor supply with respect to vacancies and wages are:

$$\frac{\partial l_{ga}(w,v)}{\partial v} = \frac{u_{ga}\lambda^U(g,a)\mu_{ga}}{V_{ga}} \cdot \frac{\delta(g,a) + \lambda^E(g,a)}{(\delta(g,a) + \lambda^E(g,a)[1 - F(w \mid g,a)])^2} \tag{B.5}$$

$$\frac{\partial l_{ga}(w,v)}{\partial w} = 2\lambda^E(g,a)f(w \mid g,a)\frac{v_{ga}u_{ga}\lambda^U(g,a)\mu_{ga}}{V_{ga}} \cdot \frac{\delta(g,a) + \lambda^E(g,a)}{(\delta(g,a) + \lambda^E(g,a)[1 - F(w \mid g,a)])^3} \tag{B.6}$$

Plugging in gives the two equilibrium conditions for optimal wage and vacancies choices for each type (ga):

$$cv_{ga}^{\eta} = (pa - w_{ga} - z_{ga})\frac{u_{ga}\lambda^U(g,a)\mu_{ga}}{V_{ga}} \cdot \frac{\delta(g,a) + \lambda^E(g,a)}{(\delta(g,a) + \lambda^E(g,a)[1 - F(w \mid g,a)])^2} \tag{B.7}$$

$$\delta(g,a) + \lambda^E(g,a)[1 - F(w \mid g,a)] = 2\lambda^E(g,a)f(w \mid g,a)(pa - w_{ga} - z_{ga}) \tag{B.8}$$

Define composite productivity as productivity net of the gender wedge, $\tilde{p}_{ga} = pa - z_{ga}$. A firm is profitable and active in any market where $\tilde{p}_{ga} \geq R(g,a)$. As in Burdett and Mortensen (1998), firms with a higher composite productivity will offer higher wages, therefore the wage distribution is a transformation of the optimal vacancy posting choices of firms:

$$F(w(\tilde{p}_{ga}) \mid g,a) = \frac{M}{V_{ga}} \int_{\tilde{p}' > R_{ga}}^{\tilde{p}_{ga}} v(\tilde{p}')d\Gamma(\tilde{p}') \tag{B.9}$$

Taking the derivative with respect to productivity gives

$$f(w(p_{ga}) \mid g,a)w'(\tilde{p}_{ga}) = \frac{M}{V_{ga}} v(\tilde{p}_{ga})\gamma(\tilde{p}_{ga}). \tag{B.10}$$

Define a system of two differential equations, one describing wages and one describing vacancies define the cdf of vacancies as

$$h(\tilde{p}_{ga}) = F(w(\tilde{p}_{ga}) \mid g,a) \tag{B.11}$$

$$h'(\tilde{p}_{ga}) = f(w(p_{ga}) \mid g,a)w'(\tilde{p}_{ga}) \tag{B.12}$$

Plugging into Equation B.8 and Equation B.7 we get:

$$w'(\tilde{p}_{ga}) = (\tilde{p}_{ga} - w(\tilde{p}_{ga}))\frac{2\lambda^E(g,a)h'(\tilde{p}_{ga})}{\delta(g,a) + \lambda^E(g,a)[1 - h(\tilde{p}_{ga})]} \tag{B.13}$$

$$h'(\tilde{p}_{ga}) = \frac{M\gamma(\tilde{p})}{V_{ga}}\left[(\tilde{p} - w(\tilde{p}))\frac{u_{ga}\lambda_{ga}^U\mu_{ga}}{cV_{ga}} \cdot \frac{\delta_{ga} + \lambda^E(g,a)}{\left(\delta(g,a) + \lambda^E(g,a)[1 - h(\tilde{p}_{ga})]\right)^2}\right]^{\frac{1}{\eta}} \tag{B.14}$$

If we assume that the gender wedge is such that $z_{ga} = 0$ for all a if $g = M$ and $z_{ga} = za$ if

$g = F$ then the least productive firm is

$$\underline{\tilde{p}}_{ga} = \begin{cases} max\{R(F,a), \underline{p} - \bar{z}\} & \text{if } g = F \\ max\{R(M,a), \underline{p}\} & \text{if } g = M \end{cases} \tag{B.15}$$

Finally, the boundary conditions to solve the system of equations are

$$\lim_{\tilde{p} \to \underline{\tilde{p}}_{ga}} w(\tilde{p}_{ga}) = R(g,a) \tag{B.16}$$

$$\lim_{\tilde{p}_{ga} \to \underline{\tilde{p}}_{ga}} h(\tilde{p}_{ga}) = 0 \tag{B.17}$$

that is the wage approaches the reservation wage and the cdf of the offer distribution approaches 0 as productivity approaches its lower limit. The level of vacancies,V_{ga} in each market is such that the pdf of the offer distribution $h'(\tilde{p}_{ga})$ integrates to 1 or equivalently

$$\lim_{\tilde{p}_{ga} \to \bar{\tilde{p}}_{ga}} h(\tilde{p}_{ga}) = 1 \tag{B.18}$$

where $\bar{\tilde{p}}_{ga}$ is $\bar{p}$ for $g = M$ and $\bar{p} - \underline{z}$ for $g = F$.

B.2.1 Solving the wage profile

Suppose we have $\underline{\tilde{p}}_{ga} = R_{ga}$ for all a and g. Then define

$$T(\tilde{p}_{ga}) = -2log(\delta(g,a) + \lambda^E(g,a)[1 - h(\tilde{p}_{ga})])$$

$$T'(\tilde{p}_{ga}) = \frac{-2\lambda^E(g,a)}{\delta(g,a) + \lambda^E(g,a)[1 - h(\tilde{p}_{ga})]}$$

and plugging into Equation B.13 we have

$$w'(\tilde{p}_{ga}) + T'(\tilde{p}_{ga})w(\tilde{p}_{ga}) = T'(\tilde{p}_{ga})\tilde{p}_{ga} \tag{B.19}$$

Multiplying by $e^{T(\tilde{p}_{ga})}$ and integrating both sides give

$$e^{T(\tilde{p}_{ga})}w(\tilde{p}_{ga}) = \int_{R(g,a)}^{\tilde{p}_{ga}} e^{T(x)}T'(x)xdx + C \tag{B.20}$$

We also have $de^{T(x)}/dx = T'(x)e^{T(x)}$, plugging in and rearranging we get

$$e^{T(\tilde{p}_{ga})}w(\tilde{p}_{ga}) = \tilde{p}_{ga}e^{T(\tilde{p}_{ga})} - R(g,a)e^{T(R(g,a))} - \int_{R(g,a)}^{\tilde{p}_{ga}} e^{T(x)}dx + C \tag{B.21}$$

$$w(\tilde{p}_{ga}) = \tilde{p}_{ga} + e^{-T(\tilde{p}_{ga})}\left[C - R(g,a)e^{T(R(g,a))}\right] - e^{-T(\tilde{p}_{ga})}\int_{R(g,a)}^{\tilde{p}_{ga}} e^{T(x)}dx \tag{B.22}$$

If the lowest productivity firm is equal to the reservation wage, then we have the boundary condition that $w(R(g,a)) = R(g,a)$. Plugging this in and solving for the constant of integration, we find that $C = R(g,a)e^{T(R(g,a))}$. Plugging in the constant of integration and the transformation $T(x)$, the wage profile becomes

$$w(\tilde{p}_{ga}) = \tilde{p}_{ga} - \int_{R(g,a)}^{\tilde{p}_{ga}} \left[\frac{\delta(g,a) + \lambda^E(g,a)[1 - h(\tilde{p}_{ga})]}{\delta(g,a) + \lambda^E(g,a)[1 - h(x)]}\right]^2 dx \tag{B.23}$$

We can now plug the wage profile into Equation B.14 to simplify the differential equation governing the distribution of vacancies:

$$h'(\tilde{p}_{ga}) = \frac{M\gamma(\tilde{p})}{V_{ga}}\left[\frac{u_{ga}\lambda^U_{ga}\mu_{ga}(\delta(g,a) + \lambda^E(g,a))}{cV_{ga}}\int_{R(g,a)}^{\tilde{p}_{ga}}\left[\frac{1}{\delta(g,a) + \lambda^E(g,a)[1 - h(x)]}\right]^2 dx\right]^{\frac{1}{\eta}} \tag{B.24}$$

B.2.2 Solving the Differential Equation of Vacancies

We can write the Equation B.24 by rewriting in a change of variables. Let

$$I(\tilde{p}_{ga}) = \int_{R(g,a)}^{\tilde{p}_{ga}}\left[\frac{1}{\delta(g,a) + \lambda^E(g,a)[1 - h(x)]}\right]^2 dx \tag{B.25}$$

Then we have the system of equations

$$\begin{aligned} h'(\tilde{p}_{ga}) &= \frac{M\gamma(\tilde{p})}{V_{ga}}\left[\frac{u_{ga}\lambda^U_{ga}\mu_{ga}(\delta(g,a) + \lambda^E(g,a))}{cV_{ga}}I(\tilde{p}_{ga})\right]^{\frac{1}{\eta}} \\ I'(\tilde{p}_{ga}) &= \left[\frac{1}{\delta(g,a) + \lambda^E(g,a)[1 - h(\tilde{p}_{ga})]}\right]^2 \end{aligned}$$

with the initial conditions $h(R(g,a)) = 0$ and $I(R(g,a)) = 0$.

C Model Estimation Appendix

C.1 Likelihood Function

We now discuss the likelihood function, starting with the contributions of unemployed and employed workers. We assume that all error terms are independent, $\nu_l^B \perp \nu_l \perp \varepsilon \perp \varepsilon^B \perp \phi^B \perp \phi$, with $l = \{u, e\}$. This implies that conditional on observable characteristics, the errors in reported wages, arrival, and separation rates are independent. For each individual i in our sample let a be the vector of observable characteristics which defines their ability a.

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

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

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

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

s_i^B, conditional on their type a and being employed is given by

$$P(p_{e,i}, n_{e,i}^B, \bar{w}_{e,i}^B, n_{e,i}, \tilde{w}_i, d_i, w_i^c | a, e_i) =$$

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

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

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

$$\begin{aligned}
\ln \mathcal{L} = \sum_{i=1}^{N} &\mathbb{1}(u_i = 1) \times [\ln P(p_{u,i}, n_{u,i}^B, \bar{w}_{u,i}^B, n_{u,i}, \tilde{w}_i|a, u_i) + \ln P(u_i|a)] \\
&+\mathbb{1}(u_i = 0) \times [\ln P(p_{e,i}, n_{e,i}^B, \bar{w}_{e,i}^B, n_{e,i}, \tilde{w}_i, d_i, w_i^c|a, e_i) + \ln P(e_i|a)], \qquad \text{(C.3)}
\end{aligned}$$

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

C.2 Distributions Derivation

This section details the distributions used to construct the likelihood function, based on the structural assumptions, as outlined in Section 4. As above, we index individuals in our sample with i and define the vector which characterizes their ability a as $\boldsymbol{a}$.

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

$$
\begin{aligned}
P(n^B_{l,i}|a) &= \int_0^\infty \frac{(\lambda^B_{l,i})^{n^B_{l,i}} \exp(-\lambda^B_{l,i})}{n^B_{l,i}!} \times f(\lambda^B_{l,i}|a)\, d\lambda^B_{l,i} \\
&= \int_0^\infty \frac{(\lambda^B_{l,i})^{n^B_{l,i}} \exp(-\lambda^B_{l,i})}{n^B_{l,i}!} \times \frac{(\lambda^B_{l,i})^{k^B_{\lambda,l}} \exp\left(\frac{-\lambda^B_{l,i}}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right)}{(\theta^B_{\lambda,l})^{k^B_{\lambda,l}} \exp(\beta^B_{l,1}a)^{k^B_{\lambda,l}}\Gamma(k^B_{\lambda,l})}\, d\lambda^B_{l,i} \\
&= \frac{1}{n^B_{l,i}!\Gamma(k^B_{\lambda,l})}\left(\frac{1}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right)^{k^B_{\lambda,l}} \int_0^\infty (\lambda^B_{l,i})^{n^B_{l,i}+k^B_{\lambda,l}-1} \exp\left[-\lambda^B_{l,i}\left(\frac{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right)\right] d\lambda^B_{l,i} \\
&= \frac{1}{n^B_{l,i}!\Gamma(k^B_{\lambda,l})}\left(\frac{1}{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right)^{k^B_{\lambda,l}} \left(\frac{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right)^{n^B_{l,i}+k^B_{\lambda,l}} \Gamma(n^B_{l,i}+k^B_{\lambda,l})
\end{aligned} \tag{C.4}
$$

$$
= \frac{\Gamma(n^B_{l,i}+k^B_{\lambda,l})}{n^B_{l,i}!\Gamma(k^B_{\lambda,l})}\left(\frac{1}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right)^{k^B_{\lambda,l}}\left(\frac{\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right)^{n^B_{l,i}} \tag{C.5}
$$

where Equation C.4 holds because $\int_0^\infty \lambda^a \exp(-b\lambda)\, d\lambda = \frac{\Gamma(a+1)}{b^{a+1}}$.

Given this, the number of job offers follows a negative-binomial distribution. The number of true arrivals is derived similarly. From Equation C.5, the probability that individual i believes they will have at least one offer is

$$
\begin{aligned}
P(p_{l,1} > 0|a) &= 1 - P(n^B_{l,1} = 0|a) \\
&= 1 - \left(\frac{1}{1+\theta^B_{\lambda,l}\exp(\beta^B_{l,1}a)}\right),
\end{aligned} \tag{C.6}
$$

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

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

$$
\begin{aligned}
P(\bar{W}^B_i \le w|n^B_{l,i}, a) &= P(\max\{W^B_{i,1}, ..., W^B_{i,n^B_{l,i}}\} \le w|n^B_{l,i}, a) \\
&= F^B(w; \mu^B_i, \sigma^B)^{n^B_{l,i}}
\end{aligned} \tag{C.7}
$$

and the pdf is

$$
P(\bar{w}^B_i|n^B_{l,i}, a) = n^B_{l,i} F^B(\bar{w}^B_i; \mu^B_i, \sigma^B)^{(n^B_{l,i}-1)} f^B(\bar{w}^B_i; \mu^B_i, \sigma^B) \tag{C.8}
$$

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

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

$$\begin{aligned} P(\tilde{w}_i|n_{l,i}, a) = &[P(w_{1,i}|n_{l,i} = 1, a)P(n_{l,i} = 1|a)]^{\mathbb{1}(n_{l,i}=1)} \\ &\times [P(w_{i,1}, w_{2,i}|n_{l,i} = 2, a)P(n_{l,i} = 2|a)]^{\mathbb{1}(n_{l,i}=2)} \\ &\times [P(w_{1,i}, w_{2,i}, w_{3,i}|n_{l,i} \geq 3, a)P(n_{l,i} \geq 3|a)]^{\mathbb{1}(n_{l,i}\geq 3)}, \end{aligned} \quad \text{(C.9)}$$

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

$$P(w_{1,i}|n_{l,i} = 1, a) = f(w_{i,1}; \mu_i, \sigma) \quad \text{(C.10)}$$

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

$$P(w_{1,i}, w_{2,i}|n_{l,i} = 2, a) = f(w_{i,1}; \mu_i, \sigma) \times f(w_{i,2}; \mu_i, \sigma). \quad \text{(C.11)}$$

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

$$P(w_{1,i}, w_{2,i}, w_{3,i}|n_{l,i} \geq 3, a) = (n_{l,i} - 2)F(w_{3,i}; \mu_i, \sigma)^{n_{l,i}-3} \prod_{j=1}^{3} f(w_{j,i}; \mu_i, \sigma). \quad \text{(C.12)}$$

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

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

$$P(s_i^B = 0|a) = \left(\frac{1}{1 + \theta_\delta^B \exp(\beta_3^B a)}\right)^{k_\delta^B}. \tag{C.13}$$

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

$$\begin{aligned} P(s_i^B \le s|a) &= P[1 - \exp(-\delta_i^B) \le s] \\ &= P[1 - \exp(-\phi_i^B \exp(\beta_3^B a)) \le s] \\ &= P\left(\phi_i^B \le \frac{-\ln(1 - s_i^B)}{\exp(\beta_3^B a)}\right) \end{aligned} \tag{C.14}$$

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

$$p(s_i^B|a) = \frac{1}{\Gamma(k_\delta^B)[\theta_\delta^B \exp(\beta_3^B a)]^{k_\delta^B}} \frac{[-\ln(1 - s_i^B)]^{k_\delta^B - 1}}{1 - s_i^B} \exp\left(\frac{\ln(1 - s_i^B)}{\theta_\delta^B \exp(\beta_3^B a)}\right). \tag{C.15}$$

For workers reporting $s_i^B = 1$, we subtract $2.2204e^{-16}$ so that Equation C.15 is real; 0.14% of the women sample and 0.45% of the men sample report a believed separation probability equal to 1.

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

$$k_\eta = \frac{\left(k_\delta \theta_\delta \exp(\beta_3 a) + k_{\lambda,e}\theta_{\lambda,e}\exp(\beta_{e,1}a)[1 - F(w_i^c; \mu_i, \sigma)]\right)^2}{k_\delta\left(\theta_\delta \exp(\beta_3 a)\right)^2 + k_{\lambda,e}\left(\theta_{\lambda,e}\exp(\beta_{e,1}a)[1 - F(w_i^c; \mu_i, \sigma)]\right)^2} \tag{C.16}$$

$$\theta_\eta = \frac{k_\delta\left(\theta_\delta \exp(\beta_3 a)\right)^2 + k_{\lambda,e}\left(\theta_{\lambda,e}\exp(\beta_{e,1}a)[1 - F(w_i^c; \mu_i, \sigma)]\right)^2}{k_\delta \theta_\delta \exp(\beta_3 a) + k_{\lambda,e}\theta_{\lambda,e}\exp(\beta_{e,1}a)[1 - F(w_i^c; \mu_i, \sigma)]}. \tag{C.17}$$

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

$$P(N_\eta(t) = 0|a) = \left(\frac{1}{1 + \theta_\eta t}\right)^{k_\eta} \tag{C.18}$$

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

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

$$P(d_i|w_i^c, a) = C[1 - P(N_\eta(d_i) = 0|a)] = C[1 - (1 + \theta_\eta d_i)^{-k_\eta}] \tag{C.19}$$

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

$$C^{-1} = \int_0^\infty 1 - (1 + \theta_\eta t)^{-k_\eta}\, dt = \frac{1}{\theta_\eta(k_\eta - 1)} \tag{C.20}$$

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

$$P(d_i|w_i^c, a) = \theta_\eta(k_\eta - 1)[1 + \theta_\eta d_i]^{-k_\eta}, \tag{C.21}$$

where k_η and θ_η are given by Equation C.16 and Equation C.17.

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

$$\mathbb{E}_\phi[\delta_i|a][1 - P(u_i|a)] = \{[\mathbb{E}_\nu[\lambda_{u,i}][1 - F_i(R_i)]\}[P(u_i|a)]. \tag{C.22}$$

Then the probability of observing worker i as nonemployed is

$$P(u_i|a) = \frac{\mathbb{E}_\phi[\delta_i|a]}{\mathbb{E}_\phi[\delta_i|a] + \mathbb{E}_\nu[\lambda_{u,i}][1 - F_i(R_i)]} = \frac{k_\delta\theta_\delta \exp(\beta_3 a)}{k_\delta\theta_\delta \exp(\beta_3 a) + k_{\lambda,u}\theta_{\lambda,u} \exp(\beta_{u,1} a)[1 - F(R_i; \mu_i, \sigma)]} \tag{C.23}$$

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

C.3 Flow value of Nonemployment

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

$$\hat{b}(a) = R(a) - \left[\hat{\lambda}_u^B(a) - \hat{\lambda}_e^B(a)\right] \int_{R(a)}^{\bar{w}} \frac{1 - \hat{F}^B(w|a)}{r + \hat{\delta}^B(a) + \hat{\lambda}_e^B(a)[1 - \hat{F}^B(w|a)]} \, dw. \tag{C.24}$$

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

$$\hat{b}(a) = c_{\hat{b}} + \beta_{\hat{b}} \cdot a + \xi \tag{C.25}$$

and estimate the equation using OLS. Column 10 of Table C.1 and Table C.2 in Appendix C.4 presents the estimated coefficients, showing that individual characteristics are associated with the flow value of unemployment of men and women in a similar way.

C.4 Parameter Estimates

Table C.1: Estimated Parameters for Women

	λ_u^B	λ_u	λ_e^B	λ_e	δ^B	δ	μ^B	μ	μ^c	b
Age 36-54	-0.026	-0.970	-0.009	0.009	-0.138	-0.643	0.058	0.017	0.139	-0.019
	(0.108)	(0.254)	(0.051)	(0.103)	(0.125)	(0.072)	(0.038)	(0.045)	(0.034)	(0.242)
Age 55-65	-0.141	-0.476	-0.077	-0.251	0.006	-1.076	0.068	-0.003	0.110	0.380
	(0.144)	(0.197)	(0.053)	(0.105)	(0.108)	(0.067)	(0.039)	(0.043)	(0.031)	(0.262)
Married	-0.108	0.178	-0.092	-0.314	-0.068	-0.119	0.239	0.167	0.161	0.323
	(0.197)	(0.162)	(0.048)	(0.079)	(0.094)	(0.064)	(0.035)	(0.036)	(0.020)	(0.161)
Child	0.217	0.319	0.071	0.273	0.414	0.014	-0.089	-0.140	-0.026	-0.947
	(0.092)	(0.208)	(0.055)	(0.085)	(0.103)	(0.067)	(0.044)	(0.030)	(0.028)	(0.194)
Some College	0.079	0.397	-0.063	-0.003	0.515	0.004	-0.145	-0.364	-0.274	-0.886
	(0.204)	(0.143)	(0.054)	(0.095)	(0.110)	(0.073)	(0.032)	(0.036)	(0.032)	(0.193)
College	0.061	0.921	-0.085	0.200	0.770	0.081	0.329	0.104	0.552	0.872
	(0.096)	(0.214)	(0.050)	(0.098)	(0.119)	(0.073)	(0.033)	(0.036)	(0.024)	(0.235)
Advanced Degree	-0.130	-0.483	-0.047	0.260	-0.333	0.260	0.576	0.253	0.727	3.380
	(0.112)	(0.394)	(0.058)	(0.115)	(0.147)	(0.073)	(0.039)	(0.046)	(0.028)	(0.300)
Race-Not White	0.344	0.465	0.143	0.228	-0.107	0.067	-0.076	-0.052	-0.056	-0.963
	(0.067)	(0.239)	(0.047)	(0.082)	(0.110)	(0.065)	(0.029)	(0.050)	(0.038)	(0.177)
Searching	0.956	1.445	0.868	0.749	-0.039	0.329	-0.139	-0.111	-0.119	-1.346
	(0.063)	(0.218)	(0.041)	(0.081)	(0.104)	(0.058)	(0.034)	(0.027)	(0.021)	(0.174)
Constant							1.357	1.154	1.816	4.150
							(0.052)	(0.063)	(0.030)	(0.344)
k	6.822	0.208	15.800	1.009	0.354	199.994				
	(1.234)	(0.030)	(4.315)	(0.046)	(0.016)	(114.999)				
θ	0.125	0.476	0.064	0.278	0.303	0.001				
	(0.027)	(0.135)	(0.017)	(0.034)	(0.041)	(0.000)				
σ							0.562	0.441	0.427	
							(0.010)	(0.013)	(0.010)	

Notes: table reports estimated coefficients for each observable characteristic, as well as parameters governing the respective error terms (when applicable) for the believed and true arrival rates when unemployed (columns 1 and 2) and when employed (columns 3 and 4), the believed and true arrival rates (columns 5 and 6), the wage offer distribution (columns 7 and 8), the current wage distribution (column 9) and the flow value of unemployment (column 10). Standard errors are reported in parentheses.

Table C.2: Estimated Parameters for Men

	λ_u^B	λ_u	λ_e^B	λ_e	δ^B	δ	μ^B	μ	μ^c	b
Age 36-54	-0.025	-0.685	0.081	-0.091	-0.118	-0.743	0.206	0.154	0.166	-0.165
	(0.191)	(0.470)	(0.045)	(0.098)	(0.126)	(0.068)	(0.039)	(0.037)	(0.027)	(0.521)
Age 55-65	-0.308	-1.137	-0.035	-0.265	1.537	-1.221	0.112	0.049	0.133	1.919
	(0.171)	(0.245)	(0.045)	(0.090)	(0.125)	(0.064)	(0.038)	(0.034)	(0.027)	(0.380)
Married	-0.006	0.249	-0.054	-0.221	0.401	-0.096	0.221	0.161	0.215	0.595
	(0.098)	(0.334)	(0.039)	(0.075)	(0.092)	(0.049)	(0.031)	(0.032)	(0.019)	(0.260)
Child	0.301	0.790	-0.018	0.027	-1.076	-0.070	0.041	-0.047	0.053	-2.554
	(0.110)	(0.361)	(0.037)	(0.072)	(0.102)	(0.047)	(0.042)	(0.038)	(0.017)	(0.529)
Some College	0.082	0.886	0.080	-0.174	-0.092	0.101	0.040	-0.245	-0.184	-0.256
	(0.120)	(0.395)	(0.051)	(0.082)	(0.133)	(0.057)	(0.038)	(0.035)	(0.023)	(0.290)
College	0.014	0.930	0.066	-0.367	-0.157	0.246	0.515	0.179	0.579	2.194
	(0.121)	(0.461)	(0.042)	(0.083)	(0.111)	(0.056)	(0.032)	(0.035)	(0.022)	(0.343)
Advanced Degree	0.060	0.550	0.005	-0.209	-0.059	0.382	0.835	0.403	0.791	3.759
	(0.140)	(0.579)	(0.053)	(0.092)	(0.130)	(0.060)	(0.035)	(0.034)	(0.031)	(0.457)
Race-Not White	0.010	0.358	0.164	0.251	-0.098	0.140	-0.143	-0.241	-0.111	1.172
	(0.099)	(0.503)	(0.040)	(0.077)	(0.107)	(0.051)	(0.029)	(0.030)	(0.020)	(0.414)
Searching	0.997	1.496	0.688	0.734	-0.257	0.290	-0.158	-0.124	-0.073	-2.662
	(0.076)	(0.282)	(0.040)	(0.067)	(0.101)	(0.052)	(0.040)	(0.026)	(0.028)	(0.307)
Constant							1.327	1.240	1.920	2.786
							(0.048)	(0.045)	(0.030)	(0.459)
k	3.949	0.240	165.624	1.108	0.305	229.603				
	(1.147)	(0.058)	(75.404)	(0.035)	(0.014)	(105.394)				
θ	0.252	0.336	0.006	0.443	0.368	0.000				
	(0.091)	(0.229)	(0.003)	(0.045)	(0.053)	(0.000)				
σ							0.565	0.441	0.451	
							(0.017)	(0.010)	(0.015)	

Notes: The table reports estimated coefficients for each observable characteristic, as well as parameters governing the respective error terms (when applicable) for the believed and true arrival rates when unemployed (columns 1 and 2) and when employed (columns 3 and 4), the believed and true arrival rates (columns 5 and 6), the wage offer distribution (columns 7 and 8), the current wage distribution (column 9) and the flow value of unemployment (column 10). Standard errors are reported in parentheses.

C.5 Perfectly Correlated Beliefs

In our baseline specification, we assumes that all error terms are independent ($\nu_l^B \perp \nu_l \perp \varepsilon \perp \varepsilon^B \perp \phi^B \perp \phi$, with $l = \{u, e\}$.). This implies that the beliefs of workers are uncorrelated with the true labor market parameters. Alternatively, we can specify that workers' beliefs are perfectly correlated with their true labor market parameters through the following structural assumptions:

$$\lambda_l(a) = \nu_l \cdot \exp(\beta_{\lambda_l} \cdot a) \qquad \lambda_l^B(a) = \exp(\beta_{\lambda_l^B} \cdot a) \cdot \lambda_l(a)$$

$$\ln w_a = c_\mu + \beta_\mu \cdot a + \varepsilon \qquad \ln w_a^B = \ln w_a + c_B + \beta_B \cdot a$$

$$\delta_a = \phi \cdot \exp(\beta_\delta \cdot a) \qquad \delta_a^B = \exp(\beta_{\delta^B} \cdot a) \cdot \delta_a$$

In this case, beliefs coincide with the true labor market parameters up to a constant that depends on ability. With these alternative structural assumptions, the likelihood function is nested inside the baseline specification and estimates 4 fewer parameters $(k_{\nu_e^B}, k_{\nu_u^B}, \sigma^B, k_{\phi^B})$.

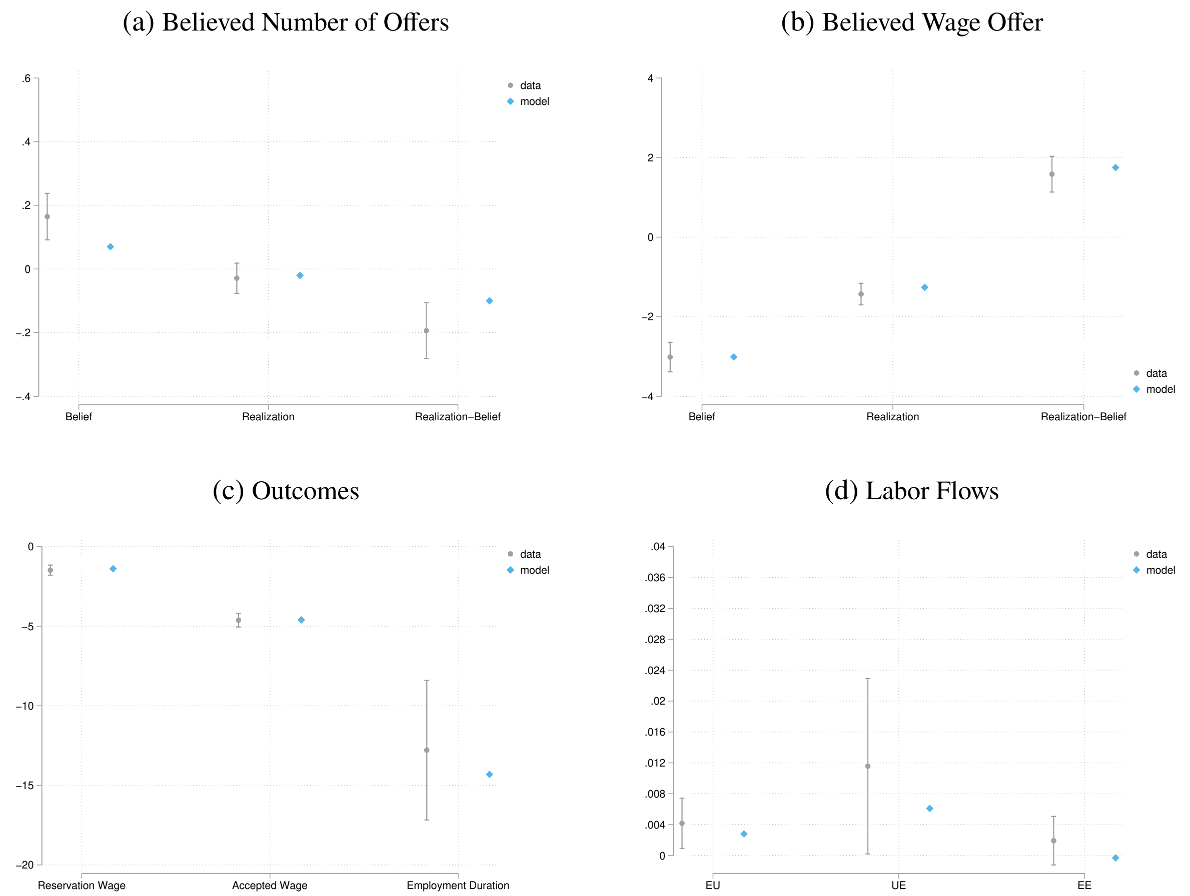
Table C.3 reports the results of a likelihood ratio test of correlated vs independent beliefs and the Akaike Information Criteria (AIC) for both models. For both genders the likelihood ratio value is well above the the critical value 13.28 for rejecting the null (perfectly correlated beliefs) at 1%. Similarly, the differences in AIC between the independent and correlated beliefs models imply that independent beliefs are a better fit for both men and women.

Table C.3: Test of Independent vs Correlated Beliefs

	Men		Women	
	Independent	Correlated	Independent	Correlated
Likelihood Value	-47221.30	-48853.00	-39693.47	-40973.86
Likelihood Ratio Value	3263.39		2560.77	
AIC	94444.61	97708.00	79584.94	82137.72
Difference in AIC	3263.39		2552.77	

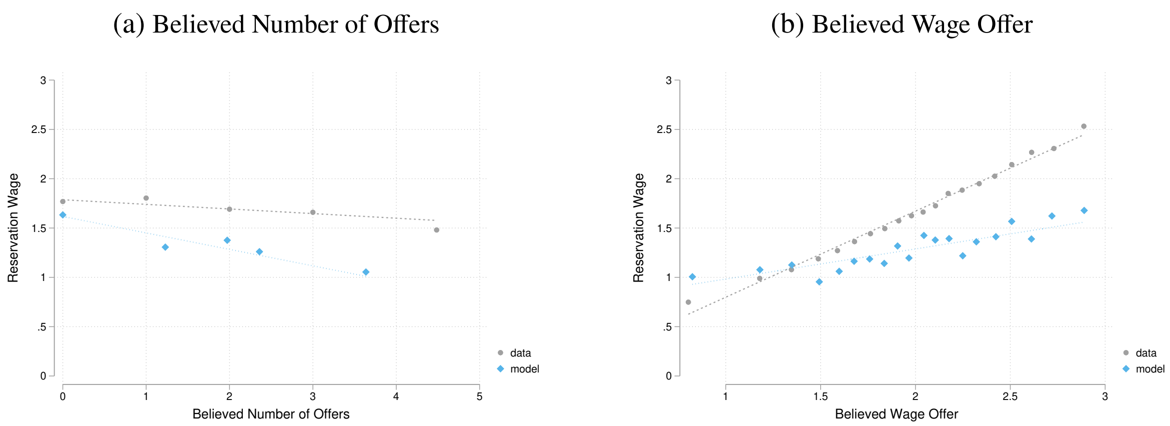
D Additional Model Validation

Figure D.1: Gender Gaps: Model vs. Data



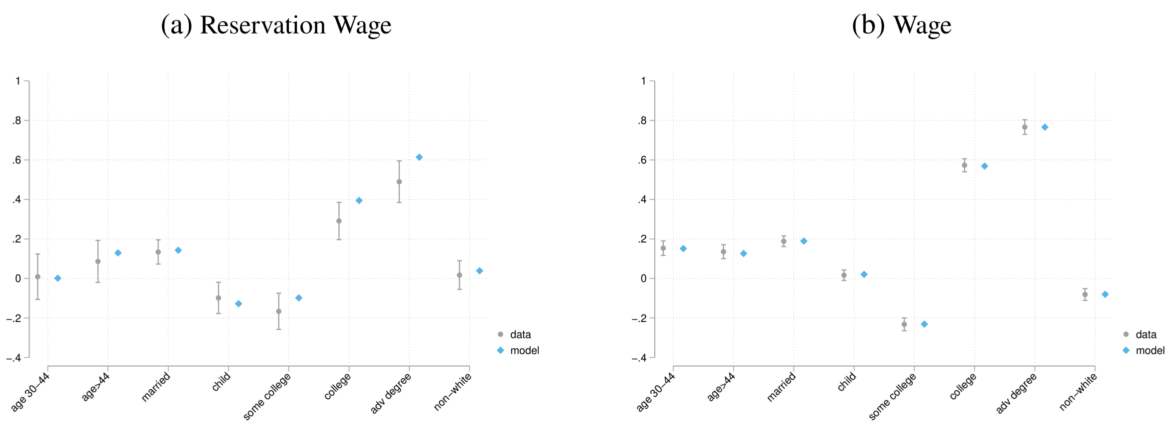
Notes: Panels report the gender gap in both the data and the model, defined as the difference between women's and men's values. Gray dots corresponds to the estimated coefficient on a female indicator from an OLS regression. Capped bars represent 95% confidence intervals. The sample is drawn from the Survey of Consumer Expectations (SCE) over the period November 2015 to November 2019, subject to the selection criteria described in Section 3.1.

Figure D.2: Reservation Wage and Beliefs: Model vs. Data



Notes: Panels (a) and (b) display binned scatter plots of reservation wages on the believed number of offers and the believed wage offer, respectively, using both data and predicted values from the model. The sample is drawn from the Survey of Consumer Expectations (SCE) over the period November 2015 to November 2019, subject to the selection criteria described in Section 3.1.

Figure D.3: Reservation Wage, Wage and Observables: Model vs. Data



Notes: Panels (a) and (b) display estimated coefficients from OLS regressions of the reservation wage and wage (in logs), respectively, on observables, using both data and predicted values from the model. Capped spikes represent 95% confidence intervals. The sample is drawn from the Survey of Consumer Expectations (SCE) over the period November 2015 to November 2019, subject to the selection criteria described in Section 3.1.

E Risk Aversion

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

$$rU^B(g,a) = \frac{b(g,a)^{1-\rho_g}}{1-\rho_g} + \lambda_u^B(g,a) \int_{R(g,a)}^{\bar{w}} \left[E^B(w,g,a)) - U^B(g,a)\right] dF^B(w \mid g,a), \tag{E.1}$$

$$rE^B(w,g,a)) = \frac{w^{1-\rho_g}}{1-\rho_g} + \lambda_e^B(g,a) \int_{w}^{\bar{w}} \left[E^B(w',g,a)) - E^B(w,g,a))\right] dF^B(w' \mid g,a) + \delta^B(g,a) \left[U^B(g,a) - E^B\right. \tag{E.2}$$

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

$$R(g,a) = \left[b(g,a)^{1-\rho_g} + (1-\rho_g)\left[\lambda_u^B(g,a) - \lambda_e^B(g,a)\right] \int_{R(g,a)}^{\bar{w}} \frac{w^{-\rho_g}(1-F^B(w|g,a))}{r+\delta^B(g,a)+\lambda_e^B(g,a)\left[1-F^B(w|g,a)\right]}\, dw\right]^{\frac{1}{1-\rho_g}}. \tag{E.3}$$

The estimation strategy remains unchanged, with the estimates of all believed and true parameters—arrival rates, wage distributions, and separation rates—remaining the same. However, we now use Equation E.3 to estimate a new set of flow values for unemployment. With risk aversion, workers have different reservation wages, so we re-estimate the productivity distribution to match the observed wage distribution with the new reservation wages.

It is well-established that men and women have different attitudes toward financial risk (Eckel and Grossman, 2002; Charness and Gneezy, 2012). Therefore, we also compute the decomposition exercise and counterfactuals for the model with different values of ρ for men and women. Following Cortés et al. (2023), who estimate risk aversion among college graduates, we set $\rho = 0.5$ for men and $\rho = 0.7$ for women. The only estimated values that change are the b-values. Table E.1 shows how the decomposition of the gender wage gap from the baseline to a model where men and women have different levels of risk aversion. Under risk neutrality (first row), biased expectations contribute about 25% to the observed gender wage gap. As expected, since risk aversion dampens the effect of expectations, the contribution from beliefs decreases, but remains substantial, accounting for 18% of the observed wage gap. The true labor market values account for 67.5% with risk aversion, and the b-values account for 13%. Differences in risk aversion account for 1% of the gender wage gap in our model.

Table E.1: Decomposition: Risk Neutrality vs. Gender Differences in Risk Aversion

		Contribution from			
	Model Wage Gap	Belief Parameters	True Parameters	b-Values	ρ
Risk Neutral	24.38	24.93	88.11	-13.04	0.00
Risk Aversion	20.19	17.89	67.57	13.35	1.19

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

Table E.2 shows how risk aversion affects the counterfactuals discussed in Section 5. Although the magnitude of the effects changes slightly with risk aversion, the overall conclusions remain: making workers unbiased about their beliefs affects the gender wage gap less than equalizing labor market opportunities. The main difference between the counterfactuals with risk aversion and risk neutrality arises in the case where workers are unbiased about their job arrival rates. In this scenario, when workers are risk-neutral, both genders' reservation wages respond significantly to changes in beliefs, but under risk aversion, beliefs matter less for reservation wages. When women are made unbiased about their arrival rates, their reservation wages respond less, keeping their wage higher than in the risk-neutral case, and decreasing the gender wage gap significantly.

Table E.2: Counterfactuals: Risk Neutrality vs. Gender Differences in Risk Aversion

	Baseline	Unbiased Beliefs				Labor Market Parameters			
		All	Arrival Parameters	Offer Productivity	Separation Rate	All	Search Rates	Firm Distribution	Separation Rate
Risk Neutral	24.38	7.63	27.40	22.60	25.68	3.65	22.31	12.57	19.31
Risk Aversion	22.15	8.98	-9.75	19.45	20.93	7.01	17.85	15.77	14.43

Notes: Table reports the model-implied wage gap in counterfactual scenarios. Baseline wage gap (column 1) is compared against the economy with unbiased beliefs (columns 2 to 5) and the economy where women's true labor market parameters are equal to those of men. The wage gender gap is defined as $100 \cdot (1 - w_f / w_m)$. *Risk Neutrality* corresponds to a model where workers are risk neutral. *Risk Aversion* corresponds to a model where women and men differ in their levels of relative risk aversion.