Discrimination, Job Search Behavior and the Gender Gap

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Abstract

Does job search exacerbate labor market gaps? Discriminated individuals may search less, leading to discouragement and widening disparities. This paper presents a matching model with endogenous job search incorporating three sources of heterogeneity for one label: employer taste discrimination, higher marginal costs of search, and higher unemployment utility. In equilibrium, discriminated workers search less, lowering their chances of future employment, necessitating less compensation, and increasing wage and employment gaps. Estimating the model to match the gender gap in the Brazilian labor market, where women search less than men, the results indicate that all three sources of heterogeneity contribute to the observed disparities at different degrees. Counterfactual exercises suggest that improving women's matching efficiency can reduce labor market gaps, especially as the data suggest not searching is worse for female employment. Additionally, the presence of children seems to impact women's search behavior.

1 Introduction and Literature

Discrimination remains a prevalent reality in labor markets worldwide. Conditional on ability, individuals' labels — for example, race, gender, country of origin, and even physical attractiveness — still lead to premiums or penalties. Since Bertrand and Mullainathan (2004) seminal paper, several studies with field experiments have shown evidence that discrimination can occur in the hiring process (see González et al. (2019), Petit (2007), Westphal (2014), and more). This paper aims to investigate the indirect general equilibrium effects (feedback effects) of employer discrimination, an area that has been understudied due to endogeneity concerns. The case study focuses on the gender gap in a large developing country, Brazil.

Job search behavior plays a crucial role in employee-employer matches and wage bargaining. However, searching incurs costs such as reviewing advertisements, sending out resumes, and more. Unemployed individuals decide to search based on whether potential future employment gains offset these costs, reflecting their expectations of future payoffs. Given the persistence of discrimination, those facing it may either oversearch (the *balancing* effect) or undersearch (the *discouragement* effect). Descriptive data for gender in Brazil suggests the discouragement effect, with women searching less than men.

Shimer (2004) and Mukoyama et al. (2018) delve into a similar job search puzzle, focusing on job search behavior during economic cycles. Shimer (2004) presents models that are compatible with pro- or counter-cyclical search responses from the unemployed and discusses that U.S. data is more consistent with the latter. On the other hand, Mukoyama et al. (2018) argue, with model and data for the U.S., that people's optimal search effort attenuates the effects of unemployment during recessions. However, these models do not consider worker heterogeneity with discrimination labels. They highlight how workers ponder future gains and may even oversearch to compensate for worse economic conditions in equilibrium.

Gender wage gaps have shown a decline but persist, even with greater educational attainment for women. The role of human capital in explaining these discrepancies seems less significant (Blau and Kahn 2017, Goldin 2014). Other factors like child penalties, social norms, and demand for flexibility have become more relevant (Kleven et al. 2019, Goldin et al. 2017). Regarding job search, Cortés et al. (2021) show that there are gender differences, with women being more risk-averse and men more overconfident. However, the impact of wage and hiring gaps on the choice of search effort is not discussed. Le Barbanchon et al. (2021) demonstrate that unemployed women have lower reservation wages, as they are less likely to commute, and family and marital status contribute to this difference.

In this paper, I propose a search and matching model based on Pissarides (2000) to investigate the dynamics of gender penalties and feedback responses in job search. The model incorporates label and ability heterogeneity, employer taste discrimination, wage bargaining, and endogenous search effort behavior. It combines characteristics of discrimination and job search models from previous literature (Borowczyk-Martins et al. 2017, Mukoyama et al. 2018). Additionally, the model includes higher marginal search costs and unemployment utility for the discriminated to assess the relevance of discrimination. In the context of gender, the marginal cost difference can be interpreted as a higher relative burden for women to search when unemployed due to commitments to housework and childcare. Descriptive data suggest that children are a significant influencing factor.

Estimating the model to match male and female moments in the Brazilian labor market reveals equilibrium wage and employment gaps: individuals with the lower label, even with the same ability, are not employed or paid as much (Borowczyk-Martins et al. 2017, Flabbi 2010). Job search patterns indicate a discouragement effect as a feedback loop of discrimination: the lower-labeled individuals, when unemployed, search relatively less, exacerbating wage and unemployment gaps and reducing their chances of remaining in the labor force. The intuition behind this effect lies in relative reservation wages, as non-discriminated individuals demand higher compensation to leave unemployment due to their higher probability of finding a job. Notably, the model results also highlight the positive contributions of divergent marginal search costs and higher unemployment utility, with the latter being particularly significant in explaining higher inactivity rates for women.

In quantitative analysis and counterfactual exercises, I find that reducing search costs through childcare policies does not significantly impact employment and wage gaps, although it should still be welfare beneficial. Another suggested policy is to increase match efficiency for women, and results show that it is successful in reducing gaps, especially in employment. These results are consistent with the literature, which highlights the importance of reducing search frictions, particularly in developing countries (Kroft and Pope 2014, Sedláček 2014, Abebe et al. 2021).

The paper is structured as follows: Section 2 presents the main model characterizing their steady-states. Section 3 presents descriptive statistics and job search in the Brazilian labor market. Section 4 details the estimation methodology and Section 5 present its results. Section 6 proposes policies to diminish the gaps and its relation to descriptive data. Finally, Section 7 concludes the study and discusses potential future directions.

2 Model

To analyze how heterogeneity can affect labor market dynamics through job search, I present a matching model with label and ability heterogeneity, wage bargaining, endogenous search, and three sources of heterogeneity between labels: employer's taste discrimination, search marginal cost, and unemployment utility.

2.1 Job Search and Meeting Rates

The model is continuous-time without uncertainty, with firms and workers discounting time by rate ρ. The economy has two states for individuals: employed or unemployed, and for firms, there are also two states: filled or empty vacancies. There is a mass 1 of individuals where u are unemployed and a number v of vacancies.

Each worker has a observable label from nature γ, either the high label γ_H or the discriminated label γ_L. p_γ is the share (and probability) of the high label in the population. Besides label, the other dimension that characterizes an individual is their ability δ. Ability δ is a continuous variable drawn from Lognormal (μ_y, σ_y) distribution. The ability's draw is independent of the label: $\gamma \perp\!\!\!\perp \delta$. I use the subscript i for the vector pair (γ, δ) that describe an individual, so $n_i \equiv n(\gamma, \delta)$ is the share of each (γ, δ) in the population. Moreover, $u_i \equiv u(\gamma, \delta)$ represents the unemployed share of individual type $i \equiv (\gamma, \delta)$ in the population.

$$p_\gamma \int_{\delta=0}^{1} n(\gamma_H, \delta) d_\delta + (1 - p_\gamma) \int_{\delta=0}^{1} n(\gamma_L, \delta) d_\delta = 1 \tag{1}$$

$$\int_{\delta=0}^{1} u(\gamma_H, \delta) d_\delta + \int_{\delta=0}^{1} u(\gamma_L, \delta) d_\delta = u \tag{2}$$

Firms are identical, and there are v vacancies available for an individual-firm meeting in the economy. Before describing how a vacancy and an individual meet, I should explain the job search in the model. The unemployed make a search effort s_i in each period. s_i is a sum of a search constant $s_0 > 0$ and a choice variable of $\hat{s}_i \geq 0$. The search effort has the downside of costing the unemployed $c(s_i)$. This is also where the first heterogeneity comes in: job search is more costly for individuals with label γ_L. γ_L individuals have an additional constant marginal cost of x, where $x > 0$.

$$s_i = s_0 + \hat{s}_i \tag{3}$$

$$c(s_i) = c_i(s_0 + \hat{s}_i) = \phi \frac{(s_0 + \hat{s}_i)^\omega}{\omega} + \hat{\mathbf{s}}_{\mathbf{i}} \mathbf{x}(\gamma), \qquad \omega > 1, \phi > 0 \tag{4}$$

$$x(\gamma) = x \times 1[\gamma = \gamma_L], \quad x > 0 \tag{5}$$

Where $\phi > 0, \omega > 1$, so the cost function is convex on s_i. The implication of the free search term s_0 is explained later. The implication of the heterogeneity in the search cost is that even when the perceived search benefit is the same for the two γ labels, γ_L individuals search less due to the additional cost.

The search benefit comes from the meeting rate of a worker with a firm. To explain this relationship, note that a meeting between an individual and the firm occurs each period following a meeting function $M(\bar{s}u, v)$, where $\bar{s}$ is the average search effort of all unemployed workers in the economy:

$$M(\bar{s}u, v) = \chi(\bar{s}u)^\eta v^{1-\eta} \tag{6}$$

$$\bar{s} = \frac{\sum_\gamma \int_\delta s_i u_i d_\delta}{\sum_\gamma \int_\delta u_i d_\delta} = \frac{\sum_\gamma \int_\delta s_i u_i d_\delta}{u} \Rightarrow \bar{s}u = \sum_\gamma \int_\delta s_i u_i d_\delta \tag{7}$$

With parameters $\chi > 0, \eta \in (0, 1)$. This function comes from Pissarides (2000). The meeting function is homogeneous of degree 1 on $(\bar{s}u, v)$ and is orthogonal to the individual index i. $\theta = \frac{v}{u}$ defines the labor market tightness. From those, I derive the meeting rate for a worker i, $\lambda_i^w(s_i, \bar{s}, \theta) \equiv s_i \times \frac{M(\bar{s}u)}{\sum_\gamma \int_\delta s_i u_i d_\delta}$, and the meeting rate for any vacancy, $\lambda^v(\bar{s}, \theta) \equiv \frac{M(\bar{s}u,v)}{v}$:

$$\lambda_i^w = s_i \frac{M(\bar{s}u, v)}{\sum_\gamma \int_\delta s_i u_i d_\delta} = s_i M\left(1, \frac{v}{\sum_\gamma \int_\delta s_i u_i d_\delta}\right) = s_i M\left(1, \frac{\theta}{\bar{s}}\right) = s_i \chi \left(\frac{\theta}{\bar{s}}\right)^{1-\eta} \tag{8}$$

$$\lambda^v = \frac{M(\bar{s}u, v)}{v} = \chi \bar{s}^\eta \theta^{-\eta} \tag{9}$$

Therefore, as search effort s_i rises in (8), it increases worker i meeting rate, λ_i^w.

2.2 Value Functions

After a meeting, the firm and worker i decide if they want to stay together. α_i is an indicator function for a successful meeting, a *match*. If there is no match, the firm has the sunk cost κ and the unemployed utility $b(\gamma)$. This is the second source of heterogeneity and to normalize, define $\xi = b_L - b_H$, where $\xi > 0$. Therefore, the value of being unemployed as a low label is higher than for high label individuals.

If employed, employees receive endogenously determined wage w_i and the firm the productivity $f(\delta), f'(\cdot) > 0$. Note that workers' productivity is only a function of their ability and not their label. However, the firm also has the third heterogeneity: taste discrimination $d(\gamma) > 0$ for the lower label γ_L, a penalty regardless of ability level (Becker 1971). Moreover, a match separation is possible and happens at rate σ.

From this setup, I can compute the value functions of firms and workers in each of their states.

- J_i is the value of a filled vacancy with worker i:

$$\rho J_i = f(\delta) - d(\gamma) - w_i + \sigma(V - J_i) \tag{10}$$

$$d(\gamma) = d \times 1[\gamma = \gamma_L], d > 0 \tag{11}$$

- V is the value of an empty vacancy:

$$\rho V = -\kappa + \lambda^v \sum_{\gamma} \int_{\delta} \frac{u_i}{u} \alpha_i (J_i - V) d_{\delta} \tag{12}$$

The free entry condition imply that $\rho V = 0$ in the model.

- W_i is the value of employment for worker i:

$$\rho W_i = w_i + \sigma(U_i - W_i) \tag{13}$$

- U_i is the value for unemployment for worker i:

$$\rho U_i = \max_{\hat{s}_i \geq 0} \{b(\gamma) - c(s_i) + \lambda_i^w(s_i)\alpha_i(W_i - U_i)\} \tag{14}$$

Therefore the individual i unemployed chooses the level of search effort $\hat{s}_i$ that maximizes its value of unemployment (14). Combining with explicit equations for search cost function (4) and meeting rate for worker (8), I arrive at the following first-order condition for an interior solution of $\hat{s}_i$:

$$\text{FOC } (\hat{s}_i) : \phi(s_0 + \hat{s}_i)^{w-1} + x(\gamma) = \frac{\partial \lambda_i^w}{\partial \hat{s}_i} \alpha_i (W_i - U_i) \tag{15}$$

$$\frac{\partial \lambda_i^w}{\partial \hat{s}_i} = \chi \left(\frac{\theta}{\bar{s}}\right)^{1-\eta} - \chi(s_0 + \hat{s}_i)(1-\eta) u_i \theta \left(\frac{\theta}{\bar{s}}\right)^{-\eta} \tag{16}$$

From (15), it's also clear that if $\alpha_i = 0$, then $\hat{s}_i{}^* = 0$ and $s_i^* = s_0$. If the unemployed know that the meeting won't be successful there is no reason to put on search effort for a higher job meeting rate.

2.3 Wage and Match Determination

From all the value functions in subsection (2.2) I can determine the match surplus of a job match, $S_i = W_i - U_i + J_i - V$. Surplus is divided by workers and firms in a Nash bargaining, where workers have power $\beta \in (0, 1)$ and the firm $1 - \beta$. This surplus split endogenously determines wages, as follows:

$$S_i = \frac{W_i - U_i}{\beta} = \frac{J_i - V}{1 - \beta} \tag{17}$$

$$\Rightarrow w_i = \beta(f(\delta) - d(\gamma) - \rho V) + (1 - \beta)\rho U_i \tag{18}$$

However, a match is formed only if $S_i > 0$. Using (17), (18) and value functions, it's possible to derive at the condition for a successful match, when $\alpha_i = 1$ and surplus is positive:

$$S_i = \frac{f(\delta) - d(\gamma) - \rho U_i - \rho V}{\rho + \sigma} \tag{19}$$

$$\Rightarrow \alpha_i = \mathbf{1}[f(\delta) - d(\gamma) - \rho U_i - \rho V \geq 0] \tag{20}$$

Therefore, in certain meetings, the gain of a match do not compensate the outside option of remaining unemployed. In appendix A.1 I prove that a meeting is successful if $f(\delta) - d(\gamma) \geq b(\gamma) - c(s_i)$. From output $f(\delta)$, a higher δ increases the chance of a successful match. In the same manner, high label γ_H workers are not associated to an employer's penalty d, hence for the same ability level δ, their match surplus are larger than γ_L individuals.

The implication of the free ("effortless") search s_0 is also introduced. As mentioned, if the surplus is negative, $\alpha_i = 0, \hat{s}_i = 0, s_i^* = s_0$, and $c(s_i) = c(s_0)$, the same for both labels as x multiplies $\hat{s}_i$. As the surplus increases with δ, there is a threshold for δ where the surplus is positive (lower for γ_H as there is no penalty). When the surplus is positive, it is now beneficial to search, however the search effort $\hat{s}_i$ is not immediately positive because of s_0. This implies that for some range of individuals even when the match exists ($\alpha = 1$) they are not searching outside of s_0 (i.e., no search effort, $\hat{s}_i = 0$). This share is important because it is observable in the data (as discussed in the data chapter 3) and used as a moment in chapter 4 estimation.

2.4 Steady State

As an equilibrium condition, the flow creation of new matches and destruction of old ones must exactly balance. From the meeting for worker i and separation rates, condition is at follows:

$$\lambda_i^w \alpha_i u_i = \sigma(n_i - u_i), \qquad \forall i \tag{21}$$

Where new matches are represented in the LHS and separations of existing matches in the RHS. As $\dot{u_i} = \lambda_i^w \alpha_i u_i - \sigma(n_i - u_i)$, in steady state, $\dot{u_i} = 0$. Equation (21) also shows that, conditional on workers with a positive surplus ($\alpha_i = 1$), an equilibrium with different meeting rates λ_w^i — which can arise with individually distinct optimal search efforts $\hat{s}_i{}^*$ — leads to different levels of unemployment u_i.

2.5 Equilibrium Definition

From past equations, I can write down the equilibrium definition with its exogenous and endogenous variables:

- Given exogenous parameters $d, \rho, \beta, b_H, \xi, \kappa, \sigma, n_i, \omega, \phi, c_0, s_0, x,$ the production function f_i, a meeting function $M(\bar{s}u, v)$, a search cost function $c(s)$, an equilibrium is a vector

  $$\alpha_i, u_i, U_i, v, s_i$$

  which solves the system of equations: the values functions of employment W_i (13) and unemployment U_i (14) (where the worker is choosing optimally the search effort), the value functions of filled and empty vacancies J_i (10) and V (12), the free-entry condition of $V = 0$, the wage bargaining determination (18), the condition for a successful meeting (20) and the zero change in unemployment $\dot{u_i}$ (21). Appendix A.2 has a gathering of all equations.

3 Data

The primary dataset for this paper is derived from the PNADC (Pesquisa Nacional por Amostra de Domicílios Contínua), a household survey conducted by IBGE since

2012. This survey serves as the official source for labor and employment data in Brazil. Approximately 210,000 households are interviewed each quarter, covering census sectors in 3,500 municipalities across all 27 regions (26 states and one federal district). Households are interviewed for five consecutive quarters, allowing the collection of panel data within a full year. This paper examines data spanning a decade, from the first quarter of 2012 to the last quarter of 2022.

In the survey, jobless individuals are asked if they are actively searching for a job. If they are not, they are asked whether they would be willing and able to take a job even if they are not actively searching. Thus, the search variable identifies those who are actively taking concrete measures to find work among a sample of unemployed individuals who want to work. This distinction is important because it provides a broader definition of "unemployment." Typically, unemployment is restricted to those actively seeking work, but here, unemployment includes all who express a desire to work, with the search variable indicating the proportion of this group that is actively searching.

3.1 Data Sample

Table 1: **Panel structure in data sample**

Quarter	Panel 1		Panel 2		Panel 3		Panel 4		Panel 5		Panel 6		Panel 7		Panel 8	
q	$\alpha = 1$	t	$\alpha = 1$	t	$\alpha = 1$	t	$\alpha = 1$	t	$\alpha = 0$	t	$\alpha = 0$	t	$\alpha = 0$	t	$\alpha = 0$	t
1	E	0							I	0						
2	E/U	1	E	0					I	1	I	0				
3			E/U	1	E	0					I	1	I	0		
4					E/U	1	E	0					I	1	I	0
5							E/U	1							I	1

Note: Panel structure applied to construct the data sample.

The survey tracks the same households for five consecutive quarters, denoted as $q = \{1, 2, 3, 4, 5\}$. I utilize the panel structure of the data for adults aged 18–65 from 2012 to 2022. The sample is constructed based on statistics from two consecutive appearances: $q = \{1, 2\}$, $q = \{2, 3\}$, $q = \{3, 4\}$, or $q = \{4, 5\}$, with no individual overlap.

The labor force sample is constructed as follows: if an individual is employed during the first appearance and is either unemployed or employed in the next period {E in

$t = 0$, E/U in $t = 1\}$, they are included in the sample as Panel 1. If an individual qualifies for Panel 1 ($q = \{1, 2\}$) but also qualifies for Panel 2 ($q = \{2, 3\}$), they are included only once, with the first two appearances being prioritized. The first four columns in Table 1 illustrate the structures for Panels 1, 2, 3, and 4 for the labor force sample, with $t = 0$ representing the first appearance as employed and $t = 1$ representing the second.

The inactive sample (out of labor force) is constructed similarly, with the restriction that the individual must be inactive (i.e., jobless and not seeking work) at both $t = 0$ and $t = 1$. Table 1 illustrates the structure of inactivity, corresponding to Panels 5–8. Again, there is no overlap if one condition for a panel applies.

3.2 Summary Statistics

Table 2 shows the summary statistics of the sample. Women are less attached to the job market, with one-third being inactive compared to only one in ten males. This detachment persists despite similar levels of education, age, and racial composition within the sample. Additionally, women work fewer hours on average, have a higher unemployment rate, and lower earnings than men. Women are also less likely to search for jobs, consistent with the model's reaction to these gaps: while 67% of jobless women willing to work actively search for employment, 72% of men do.

3.3 Wage and Unemployment Gaps in the Data

As Table 2 suggests, the data confirm employment and wage gaps in the Brazilian labor market. Since the sample is restricted to those employed at $t = 0$, it is possible to analyze gaps in $t = 1$ across the wage distribution of $t = 0$. Figure 1 shows that women are more likely to be unemployed regardless of previous earnings percentile. Additionally, women's earnings are lower than men's across the entire earnings distribution, with gaps increasing at higher earnings levels.

In summary, gender wage and employment gaps are evident in the Brazilian labor market. Addressing the central question of the paper, what should be the job search choices of men and women? There appears to be a discouragement effect, where women search less due to lower expected returns and the high costs of job searching.

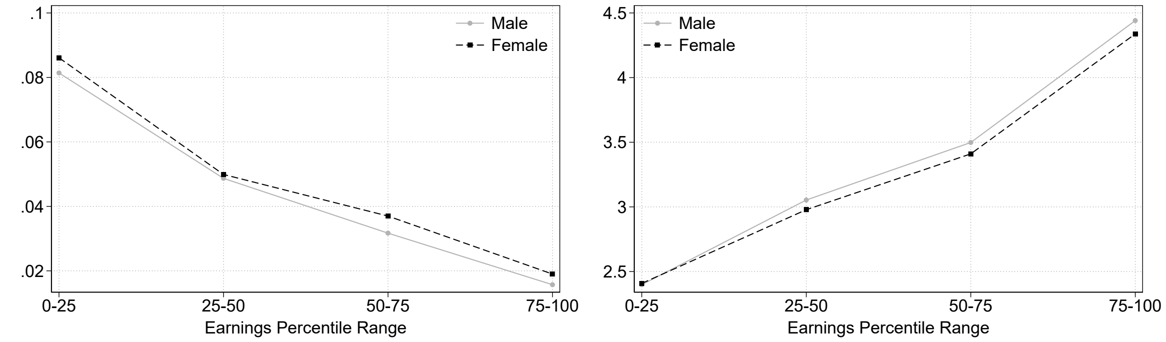
Table 2: **Summary Statistics**

	Male	Female
Share	0.51	0.49
Age	38.9	40.0
	(12.4)	(12.7)
Years of schooling	10.1	10.6
	(4.3)	(4.4)
White	0.47	0.49
	(0.5)	(0.5)
Unemployed	0.045	0.049
	(0.21)	(0.22)
Hours	42.5	37.7
	(11.8)	(10.7)
Formality status	0.63	0.67
	(0.48)	(0.47)
Earnings, per hour	43.9	39.0
	(70.8)	(55.8)
Partner earnings, per hour	34.0	47.3
	(65.9)	(82.9)
Has partner	0.84	0.76
Household has child	0.75	0.78
Inactive share (out of laborforce)	0.10	0.34
Searching, if jobless and willing to work	0.72	0.67
Number of observations	1015719	1009576

Note: Average and standard deviations, by gender, at $t = 0$. 18–64 years old. For searching, the denominator is those unemployed and willing to work at $t = 1$. For unemployment, the proportion is also calculated at $t = 1$. Source: PNADC 2012-2022.

According to the model, the primary sources of these gaps could be a combination of discrimination, higher search costs for women, and the endogenous response to these disparities exacerbating the discrepancies.

Figure 1: **Unemployment and wage gaps**
By earnings percentile range when employed at $t = 0$



(a) Unemployment rates at $t = 1$ (b) Real log earnings at $t = 1$

Note: Individuals aged 18–65. Percentiles were calculated separated by gender. Source is PNADC 2012-2022.

4 Estimation

4.1 Econometric Specification

The production function is represented by the random variable δ. δ denotes an individual's productivity disturbance, drawn from a Lognormal(μ_y, σ_y) distribution, independent of the label γ_H (men) and γ_L (women).

$$f(\delta) = \delta \ , \qquad \delta \sim \text{Lognormal}(\mu_y, \sigma_y) \tag{22}$$

The estimated parameters form the set Θ_0:

$$\Theta_0 = \{d, x, \mu_y, \sigma_y, \omega, s_0, \phi\} \tag{23}$$

The remaining relevant parameters are calibrated as shown in Table 3. The share of each label p_γ is 0.5, consistent with Table 2. The discount rate $\rho = 0.05$ reflects an impatience rate of 0.95. The separation rate $\sigma = 0.04$ aligns with data indicating a 4% unemployment probability if employed at $t = 0$. Parameters for the meeting function ($\eta = 0.9$, $\chi = 0.9$) and unemployment instant utility $\{b_H, \xi\}$ are arbitrarily chosen to facilitate estimation. However, ξ is allowed to vary among six different predetermined values, which will be explained in more detail later.

Using these parameter values and drawing δ, the model solves for the endogenous variables. The primary interest lies in wages, the unemployment rate u_i, search effort $\hat{s}_i$, and the inactivity share $\alpha_i = 0$. The estimation aims to match these moments with their respective observables in the data by gender.

Table 3: **Parameters**

p_γ	0.5	Share of high type in population
b_H	2.0	Unemployment instant utility
ρ	0.05	Discount
σ	0.04	Separation rate
β	0.5	Worker's bargaining power
η	0.9	Parameter in meeting function
χ	0.9	Parameter in meeting function
$f(\delta) = \delta$		Production function
Θ_0 :		
d	–	Employer's taste discrimination
x	–	Difference in marginal search cost
κ	–	Cost of empty vacancy
μ_y	–	Parameter of Lognormal
σ_y	–	Parameter of Lognormal
ω	–	Parameter in cost function
ϕ	–	Parameter in cost function
s_0	–	Free search

To achieve this, I employ the Simulated Method of Moments (SMM) as the estimator. First, I calculate empirical moments $\hat{\boldsymbol{m}}_N$ from the data. Estimated parameters are then obtained by minimizing the following function:

$$L_N(\boldsymbol{\theta}) = \frac{1}{2}\left(\hat{\boldsymbol{m}}_N - \boldsymbol{m}^S(\boldsymbol{\theta})\right)' \Omega^{-1} \left(\hat{\boldsymbol{m}}_N - \boldsymbol{m}^S(\boldsymbol{\theta})\right) \tag{24}$$

Here, $\boldsymbol{m}^S(\boldsymbol{\theta})$ represents the vector of model-generated moments, and $\hat{\boldsymbol{m}}_N$ corresponds to the empirical moments. The weight matrix, denoted as Ω^{-1}, is defined so that a one-unit deviation in log real earnings is penalized equally to a one-percentage-point deviation in rate variables (unemployment, search, and inactivity). More detailed of Ω^{-1} in the appendix A.4.

4.2 Moments

The selected empirical moments are introduced in Chapter 3. They include unemployment shares and average log real wages, categorized by gender and previous wage percentiles. Overall active search and inactive shares are also considered. In the model, the inactive share is the proportion of the population with negative surplus ($\alpha_i = 0$). Active search is identified by those with positive surplus who have zero search effort ($\alpha_i = 1$ and $\hat{s}_i = 0, s_i = s_0$). Table 4 summarizes all moments.

Table 4: **Data moments, by previous wage percentiles**

Average Real Wages (log)				Unemployment Rates (%)				Inactive (%)	Search (%)
0-25	**25-50**	**50-75**	**75-100**	**0-25**	**25-50**	**50-75**	**75-100**		
				Male (γ_H):					
2.40	3.05	3.50	4.44	8.14	4.87	3.17	1.57	34.2	72.0
				Female (γ_L):					
2.41	2.98	3.41	4.34	8.61	4.99	3.70	1.90	10.0	67.2

4.3 Identification of Heterogeneity

In the model, there are three sources of heterogeneity: employer taste discrimination, higher marginal search cost, and higher unemployment utility for individuals with the lower label (women), γ_L. All three factors lead to differences in unemployment, wages, and search efforts. However, the difference in inactivity rates (34.2% for women vs. 10% for men) can only be explained by a positive discrimination penalty or unemployment utility gap. As shown in Appendix A.1, the condition for a positive surplus is:

$$f(\delta) - d(\gamma) > b(\gamma) - c(s_i^*) \tag{25}$$

Suppose there is no penalty and unemployment utility gap, so $d = 0$ and $\xi = 0$. Define the productivity thresholds for positive surplus for high label as δ_H^T and low label as δ_L^T. The higher the productivity threshold the higher the inactivity share, meaning your ability needs to increase in order for a match to be successful. At equality of surplus equal to zero, $\hat{s}_i = 0$ and $s_i^* = s_0$ for both labels because of the free search, as explained in chapter 3. That implies that the productivity thresholds for positive surplus are the same, $\delta_H^T = \delta_L^T$:

$$f(\delta_H^T) = b - \phi \frac{s_0^\omega}{\omega} = f(\delta_L^T) \tag{26}$$

By contrapositive, the difference in inactivity share is solely explained if either $d > 0$ or $\xi > 0$.

4.3.1 Unemployment instant utility b

In the gender literature, there is a discussion about whether b, the flow utility of unemployment, is the same between genders. The value of b can represent, for example, wealth or partner earnings. It is reasonable to assume that b is greater for women in the data, as Table 2 shows that partner earnings are higher for women, even though a lower percentage of them are married. This suggests that the share of inactivity among women is not solely explained by a discrimination penalty but also by a more substantial outside option for women.

As equation 27 shows, if b is greater for women, then the inactivity share becomes higher for women even with $d = 0$ as the reservation wage rises. Suppose $\xi > 0, b_L > b_H$:

$$f(\delta_H^T) = b_H - \phi \frac{s_0^\omega}{\omega} < b_L - \phi \frac{s_0^\omega}{\omega} = f(\delta_L^T) \tag{27}$$

For identification purposes of d, the estimation adopted is as follows. I estimate the full model varying the calibration of $\xi = b_L - b_H$, with $\xi = \{0, 0.1, 0.15, 0.3, 0.45, 0.6\}$, so that a predetermined part of the inactivity gap is left to be explained by d. The estimation resulting in the lowest mean squared error (MSE) of all six versions is the preferred one.

5 Results

The results of the estimations are presented in Table 5. The main parameters are the heterogeneities: the discrimination penalty d and the marginal cost of search x, both applying to women. Positive results were found for both parameters.

Table 5: **Model: estimated parameters**

	μ_y	σ_y	s_0	κ	ω	ϕ	d	$\bar{\xi}$	x
Model 1	5.67	0.376	1.17	225	2.558	0.081	0.073	$\bar{\xi} = 0.00$	0.18
Model 2	5.67	0.373	1.22	225	2.453	0.089	0.077	$\bar{\xi} = 0.10$	0.13
Model 3	5.68	0.367	1.21	225	2.487	0.091	0.086	$\bar{\xi} = 0.15$	0.11
Model 4	5.69	0.361	1.22	221	2.266	0.117	0.089	$\bar{\xi} = 0.30$	0.07
Model 5	5.71	0.345	1.33	219	2.243	0.122	0.093	$\bar{\xi} = 0.45$	0.03
Model 6	5.72	0.355	1.38	217	2.201	0.134	0.113	$\bar{\xi} = 0.60$	0.00

Note: Averages of 100 simulations for each model with N=3000 individuals for simulated method of moments.

As the unemployment utility b for women increases relative to men's (ξ increases), the estimated penalty increases while the additional marginal cost decreases. At first, this may seem counterintuitive, but it aligns with job search theory. As the outside option for women increases, their inactivity share rises, but their wages should also increase due to higher reservation wages. To reconcile this with the observed gender wage gap in the data, the penalty increases, as it more directly affects wages than the marginal cost of search. Consequently, an increase in the penalty d leads to a lower x, as more of the unemployment and wage heterogeneities are accounted for.

Table 6 in the appendix presents the moments based on the estimated values. The first column contains the data moments for comparison. The model with the lowest mean squared error is Model 5, where the discrimination penalty, women's additional marginal search cost, and the additional women's flow utility are $\{d, x, \xi\} = \{0.093, 0.03, 0.45\}$. For the subsequent analysis, Model 5 serve as the baseline.

5.1 Baseline Model

Figure 2 displays the steady-state outcomes for key variables. Panel (a) shows the difference in inactivity shares: women require a higher ability level to achieve a positive surplus. Panels (b) and (d) represent the employment and wage gaps: for the same ability δ, there is an interval where women (γ_L) are not employed, and if they are, they earn less. Optimal search effort values are shown in panel (e), with the vertical line indicating when the surplus becomes positive.

There is evidence of a discouragement effect in equilibrium: discriminated women, γ_L, search less even when they can be employed. The difference in optimal search $\hat{s_i}^*$ across individuals explains the unemployment share gap between high and low labels in panel (d), as their meeting rates are lower. This also accounts for the increasing wage gap as ability rises. Therefore, employer taste discrimination and higher marginal cost effects are amplified through job search, exacerbating wage and employment disparities.

5.2 Impact of Heterogeneity Sources

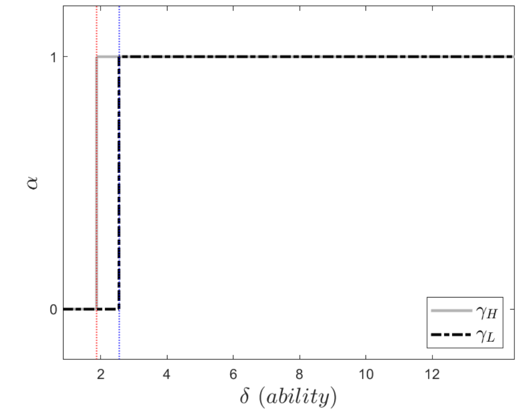
Using the baseline model, Figure 3 shows the impact of three sources of heterogeneity on wage gaps. In each scenario, one source of heterogeneity is set to zero. The goal is to analyze the sensitivity of each factor in creating gaps, not necessarily to suggest policy implications, as reducing unemployment utility isn't inherently beneficial for women, even if it results in higher employment. The scenarios are:

- $\{d, x, \xi\} = \{0, 0.03, 0.45\}$
- $\{d, x, \xi\} = \{0.093, 0, 0.45\}$
- $\{d, x, \xi\} = \{0.093, 0.03, 0\}$

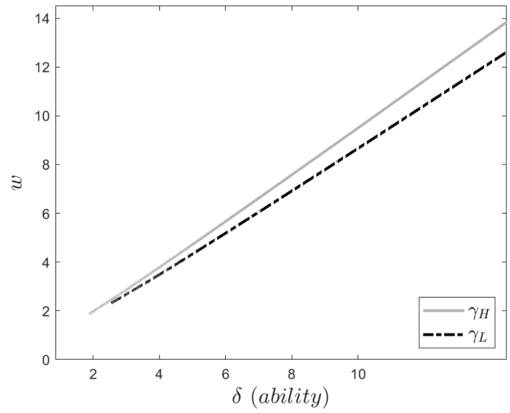
Panel (a) clearly shows that the wage gap is highly elastic to the discrimination penalty. The effects of search costs and the value of unemployment are indirect and operate in different directions. Among these factors, eliminating the marginal cost γ_L has almost no effect on wage gaps. Even for the search gap itself, panel (c) demonstrates that the impact of marginal search cost is lower than that of the other two sources of heterogeneity.

For employment, panel (b) illustrates that eliminating either the women's advantage in unemployment utility or the discrimination penalty reduces the unemployment gap. Comparatively, the penalty reduction has a greater impact at higher ability levels than at lower ability levels.

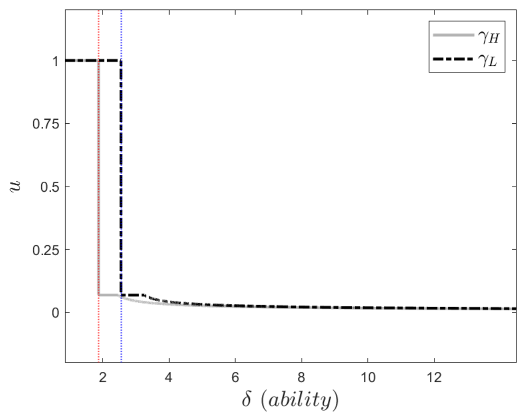
Figure 2: Baseline model, equilibrium



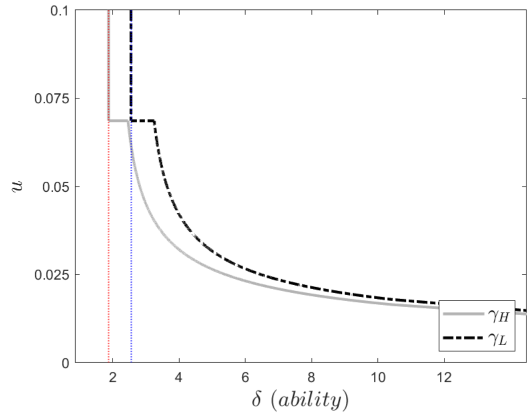
(a) α_i = Surplus > 0



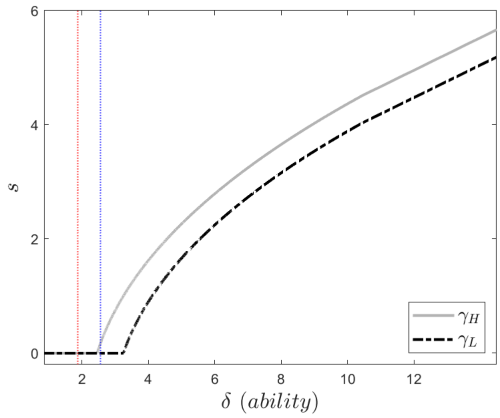
(b) w_i



(c) Share unemployed u_i



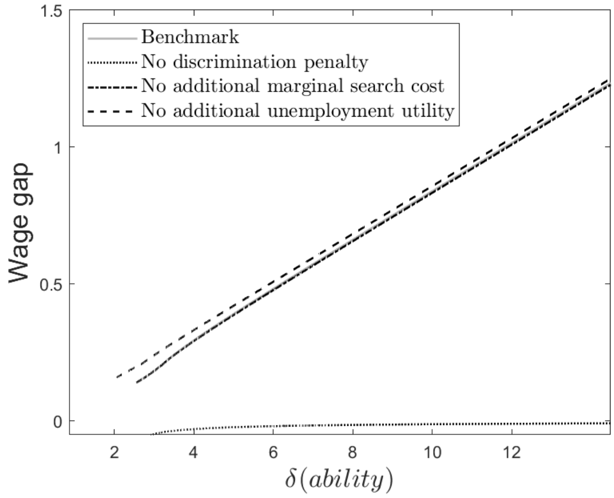
(d) Share unemployed (zoom) u_i



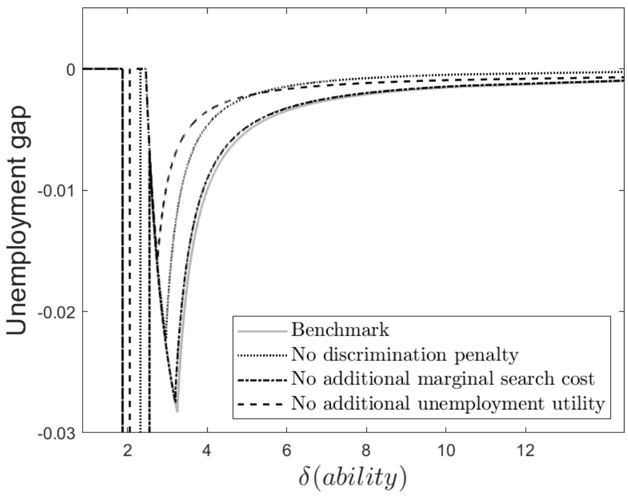
(e) Search s_i

Note: Panels display graphical numerical representation of baseline model equilibrium.

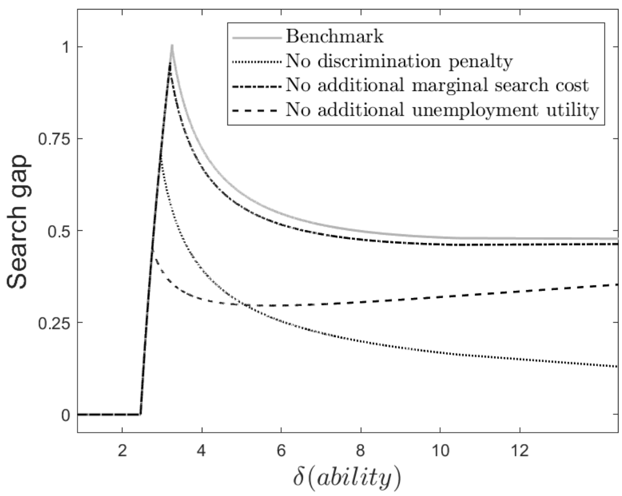
Figure 3: Models eliminating heterogeneity sources, gaps



(a) $w(\gamma_H) - w(\gamma_L)$



(b) $u(\gamma_H) - u(\gamma_L)$



(c) $\hat{s}(\gamma_H) - \hat{s}(\gamma_L)$

Note: Panels display graphical numerical representation of models equilibrium gaps.

6 Counterfactual Policies and Discussion

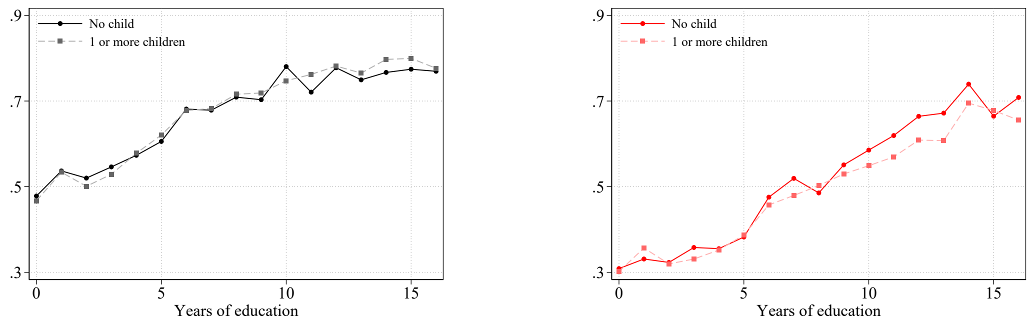
Using the baseline model, this chapter presents counterfactuals based on possible policies and baseline model results aimed at reducing wage and employment gaps. Additionally, I discuss these policies based on evidence from the data and their correlation with job search behavior.

6.1 Children and Search Cost

In line with this paper's model, it is more costly for women to search for jobs ($x > 0$). This higher cost is partly due to cultural expectations that women allocate more time to childcare. Therefore, one group experiences a higher opportunity cost of job search due to dedicating time to childcare.

To investigate these correlations in the data, Figure 4 displays the search behavior for men (panel a) and women (panel b) with and without children by years of education. The lines for men remain essentially the same, indicating that children have no discernible impact on their job search. However, for women, there is a noticeable gap, particularly among those with 9 to 14 years of education, where women are more represented. Table 7 in the appendix presents the results of a simple Linear Probability Model (LPM) analysis, controlling for rich covariates, which corroborate the findings in the graphs. The presence of children penalizes women even more in terms of their chances of engaging in active job search.

Figure 4: **Active Job Search and Children**
Over workers unemployed willing & able to work right away



(a) Men (b) Women

Source: PNADC 2012-2022. 1 = is actively searching. 18–65 years old individuals.

It is important to note that parents might differ from childless individuals in unobservable ways. Nonetheless, anecdotal evidence suggests that children are a significant factor influencing job search behavior causally. In the survey, interviewers also ask the reasons for not searching. The most common reason for both genders is "there is no job close by," although it is more prevalent among men (59% vs. 42%). However, the crucial difference lies in the reasons related to housework and childcare: 16% of non-searching women cited these duties, compared to only 1% of males.

A policy aiming to decrease the cost of search for women is to improve accessibility to childcare. The first counterfactual scenario involves reducing the marginal search cost by 50%.

$$c(s_i) = \begin{cases} \phi \frac{s_i^{\omega}}{\omega}, & \text{if } \gamma = \gamma_H \\ \phi \frac{s_i^{\omega}}{\omega} + \hat{s}_i \frac{x}{2}, & \text{if } \gamma = \gamma_L \end{cases} \tag{28}$$

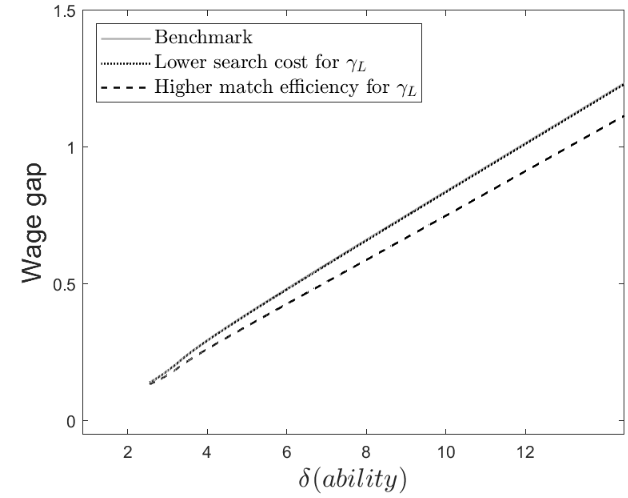
As shown in Figure 5 and discussed in Section 5.2, reducing search costs has only a modest impact on reducing wage and employment gaps. However, this does not imply a decrease in welfare for women. In fact, reducing search costs increases women's utility when unemployed. Moreover, if the childbearing burden in society becomes more balanced between women and men, and employers' perceptions of gender change accordingly—specifically, if employers no longer expect female employees to commit more to housework and childcare—this could indirectly affect matching efficiency or the discrimination penalty.

6.2 Matching Efficiency

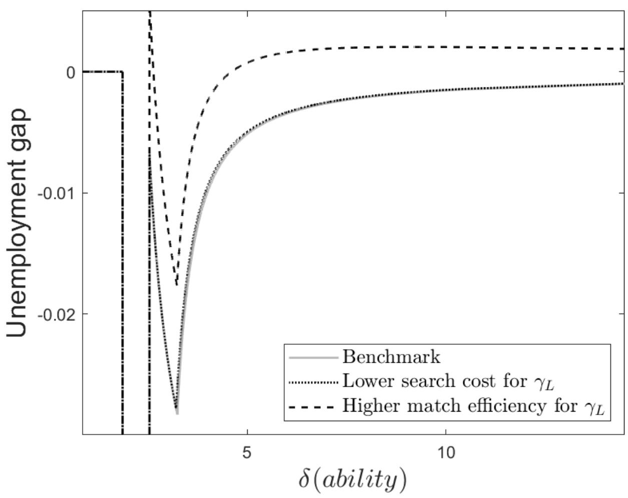
The second proposed policy is to increase match efficiency for women relative to men. Job search literature has discussed its importance in reducing frictions and improving labor market outcomes (Kroft and Pope 2014, Sedláček 2014). Developing economies suffer more from an asymmetry of information or search frictions in the matching process (Abebe et al. 2021), making it even more challenging for unemployed women in Brazil who are not actively searching to find good jobs.

Exploiting the panel and the transition sample, I investigate if the data shows that searching relates to differences in outcomes for each gender separately. I follow

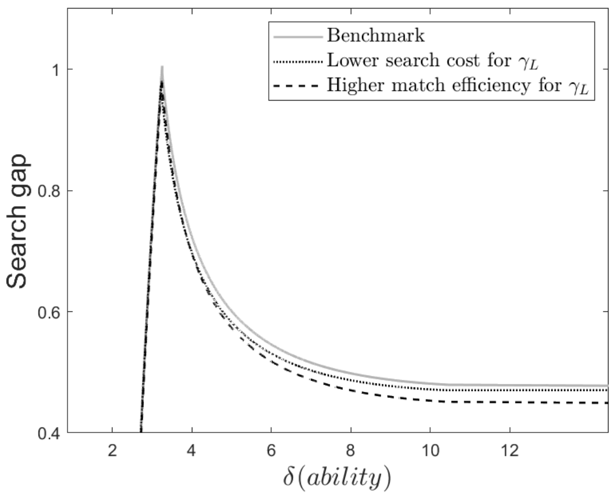
Figure 5: Counterfactuals models, gaps



(a) $w(\gamma_H) - w(\gamma_L)$



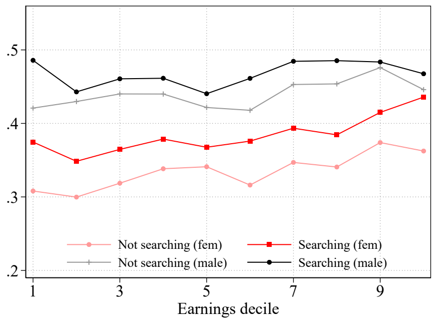
(b) $u(\gamma_H) - u(\gamma_L)$



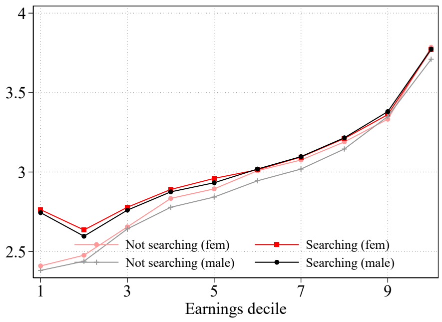
(c) $\hat{s}(\gamma_H) - \hat{s}(\gamma_L)$

Note: Panels display graphical numerical representation of models equilibrium gaps.

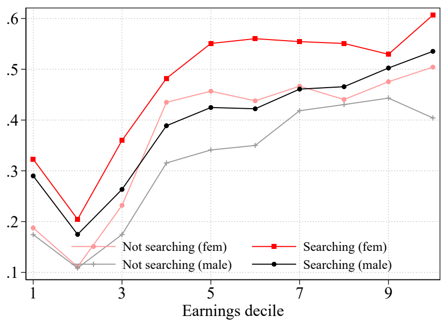
Figure 6: Consequences of not searching, by gender



(a) Found a job



(b) Wages, cond. on job



(c) Formal job, cond. on job

Dependent Variable: **Outcomes** *(OLS regressions)*	Find a job in $t+1$		Wages in $t+1$, cond on job		Formal in $t+1$, cond on job	
	Men	Women	Men	Women	Men	Women
Searching in t, when jobless	0.0230***	0.0450***	0.0739***	0.0476***	0.0408***	0.0343***
	(0.0046)	(0.0048)	(0.0077)	(0.0097)	(0.0058)	(0.0075)
Log last earnings	0.0255***	0.0396***	0.4146***	0.4014***	0.0727***	0.0742***
	(0.0033)	(0.0035)	(0.0056)	(0.0071)	(0.0042)	(0.0055)
Constant	0.5283***	0.2746***	1.1843***	1.2881***	-0.2323**	-0.0429
	(0.0797)	(0.0564)	(0.1241)	(0.1089)	(0.0934)	(0.0842)
Region FE	x	x	x	x	x	x
Quarter x Year FE	x	x	x	x	x	x
Age FE	x	x	x	x	x	x
Years of Education FE	x	x	x	x	x	x
Observations	55,062	45,009	27,385	16,621	27,389	16,628
Adjusted R-squared	0.049	0.036	0.404	0.402	0.134	0.175

Source: PNADC 2012-2022. 18–65 years old individuals who lost their jobs after $q = 1$.

an individual for three consecutive quarters out of the five observable ones. The restriction is that in the first chosen quarter $t = 0$ (either $q = \{1, 2, 3\}$), the individual should be employed, and in $t + 1$, they should be unemployed and willing and able to have a job. I run regressions for outcomes in $t + 2$ with an indicator for having searched or not in the previous quarter, $t + 1$.

$$y_{ig,t+2} = \alpha + \beta(S_{ig,t+1}) + X_{igt} + \epsilon_{ig,t+3}, \quad g = \{\text{Women, Men}\} \tag{29}$$

This allows control for covariates, including children, and the individual's last job characteristics seen in t, including last earnings. I run separate regressions for men and women. The regression results and a simple descriptive statistic are shown in Figure 6. Clearly, not searching has negative implications for both men and women regarding chances of employment. Moreover, it is detrimental to wages and formality, conditional on employment. Comparing point estimates of both genders, not searching is worse for women (a decrease in employment probability of around 5% vis-a-vis 2%). However, the search penalty seems to be less relevant for women when it comes to wages. These data results highlight the link between job search behavior and eventual labor market outcomes of interest.

In this paper's exercise, to analyze how match efficiency can be relevant, I alter the model benchmark set at $\chi = 0.9$. I run counterfactuals of labor market outcomes increasing women's efficiency by 5% relative to men, at $\chi = 0.945$. A policy aiming at this improvement could include:

- Enhancing access to online platforms that inform about available vacancies.
- Subsidizing women's transport costs for interviews.
- Encouraging training programs for women that provide more accurate information to employers during recruitment.

$$M(\bar{s}u, v) = \chi(\bar{s}u)^{\eta} v^{1-\eta} \begin{cases} \chi = 0.9, & \text{if } \gamma = \gamma_H \\ \chi = 0.945, & \text{if } \gamma = \gamma_L \end{cases} \tag{30}$$

Figure 5 highlights the impact of this policy. The results show that a 5% increase in matching efficiency is significant in reducing both the unemployment gap and wage gaps, especially the former. It also reduces job search gaps, aligning with the evidence on how job search interacts with match meeting efficiency.

7 Conclusion

Attributes (labels) of nature, even when controlling for ability and productivity, continue to significantly influence labor market outcomes, resulting in clear racial and gender gaps. While the labor economics literature has explored various explanations for this phenomenon, a compelling question remains: given the existence of discrimination, how do individuals (labels) react?

Job search is a crucial stage in this process, as outcomes depend on the costly search efforts of unemployed individuals. In this paper, I present a search and matching model that incorporates a surplus penalty (taste discrimination) for a particular label. The model also introduces other sources of heterogeneity to understand their relevance to job search behavior and gaps, such as higher marginal search costs and higher unemployment utility for the discriminated. The results reveal the presence of wage and employment gaps, with endogenous job search behavior highlighting a discouragement effect: discriminated labels search less. Consequently, when employed, the wage gap is more pronounced and increases with productivity.

Estimating the model to match data moments from the Brazilian labor market and gender differences supports the presence of wage and employment gaps and underscores the relevance of the discrimination penalty. The model demonstrates that women search less than men and have a higher chance of being out of the labor force. Reduced-form analysis in the data corroborates that job search influences future employment and wages for both genders.

The impact of children on women's search decisions suggests that searching can be more costly for them, independent of discrimination. Quantitative analysis shows that reducing search costs does not significantly impact wage and employment gap reduction directly, although it can be indirectly significant if it affects the discrimination penalty or match efficiency. Reducing search frictions appears to be very relevant to addressing gender and employment gaps, especially the latter. This study seeks to contribute to a deeper understanding of how to address unfair discrepancies in labor market outcomes and identify effective ways to reduce them.

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A Appendix

A.1 Condition for a successful meeting

A meeting is successful if $\alpha_i = 1 \Rightarrow f(\delta) - d(\gamma) - \rho U_i - \rho V > 0$. As $V = 0$ from the free-entry condition, above condition holds if $f(\delta) - d(\gamma) > \rho U_i$. Using the isolated equation of value of unemployment (34) and considering that $\alpha_i = 1$:

$$f(\delta) - d(\gamma) > \frac{b(\gamma) - c(s_i^*) + \frac{\beta\lambda^w}{\rho+\sigma}(f(\delta) - d(\gamma))}{1 + \frac{\beta\lambda^w}{\rho+\sigma}}$$

$$\Rightarrow f(\delta) - d(\gamma) > b(\gamma) - c(s_i^*) \tag{31}$$

Alternatively, if $\alpha_i = 0$, then $\rho U_i = b(\gamma) - c(s_i^*)$, as expected.

A.2 Model 1: equilibrium definition

Given exogenous parameters $d, x, \rho, \beta, b_H, \xi, \kappa, \sigma, n_i, \omega, \phi, s_0$, the production function f_i, a meeting function $M(\bar{s}u, v)$, a search cost function $c(s)$, an equilibrium is a vector

$$\alpha_i, u_i, U_i, v, s_i \tag{32}$$

that solves the system of equations:

$$V = \frac{-\kappa + \frac{\lambda^v(1-\beta)}{\rho+\sigma}\sum_\gamma \int_\delta \frac{u_i}{u}\alpha_i(f(\delta) - d(\gamma) - \rho U_i)d_\delta}{\rho + \frac{\rho\lambda^v(1-\beta)}{\rho+\sigma}\sum_\gamma \int_\delta \frac{u_i}{u}\alpha_i d_\delta} = 0 \tag{33}$$

$$U_i = \frac{b(\gamma) - c(s_i^*) + \frac{\beta\lambda_i^w}{\rho+\sigma}\alpha_i(f(\delta) - d(\gamma) - \rho V)}{\rho + \frac{\rho\beta\lambda_i^w}{\rho+\sigma}\alpha_i} \tag{34}$$

$$\hat{s_i}^* = \underset{\hat{s_i}^* \geq 0}{\arg\max} \; \frac{b(\gamma) - c(s_i^*) + \frac{\beta\lambda_i^w(\hat{s_i}^*)}{\rho+\sigma}\alpha_i(f(\delta) - d(\gamma) - \rho V)}{\rho + \frac{\rho\beta\lambda_i^w(\hat{s_i}^*)}{\rho+\sigma}\alpha_i} \tag{35}$$

$$s_i = s_0 + \hat{s}_i \tag{36}$$

$$\bar{s} = \frac{\sum_{\gamma} \int_{\delta} s_i d_{\delta}}{u} \tag{37}$$

$$\lambda^w \alpha_i u_i = \sigma(n_i - u_i) \quad \forall i \tag{38}$$

$$u = \sum_{\gamma=\gamma_L,\gamma_H} \int_{\delta} u_i d_{\delta} \tag{39}$$

$$\alpha_i = \mathbf{1}[f(\delta) - d(\gamma) - \rho U_i - \rho V > 0] \tag{40}$$

$$\lambda^w(s_i, \bar{s}, u, v) = s_i \frac{M(\bar{s}u, v)}{\sum_{\gamma} \int_{\delta} s_i u_i d_{\delta}} \tag{41}$$

$$\lambda^v(\bar{s}, u, v) = \frac{M(\bar{s}u, v)}{v} \tag{42}$$

Where equation (33) comes from value equations of filled and empty vacancies (10), (12), the free entry condition $V = 0$ and wage bargaining solution (18); whereas equation (34) comes from value equations of employment and unemployment (13), (14) and wage bargaining solution (18).

A.3 Algorithm

The following algorithm is used in programming to estimate and find the equilibrium:

1. Discretize the ability δ support from a Lognormal (μ_y, σ_y) distribution.

2. Set values of model's parameters and guess initial values for equilibrium variables $v, u, u_i, \alpha_i, \bar{s}$.

3. With those values, solve for the optimal search effort. Find optimal $\hat{s}_i{}^*$ that maximizes the maximum value of unemployment U_i from (34). Also, compute this maximum value of U_i.

4. With U_i and $V = 0$, check the surplus of a meeting from (20) and reconstruct α_i.

5. After finding α_i and with $\hat{s_i}^*$ from previous steps, find the other equilibrium variables $u, v, u_i, \bar{s}$ that solve (33), (38), (39), (37), (41) and (42).

6. Iterate until $u, v, u_i, \bar{s}$ converge and match initial values.

A.4 Estimation Equation

The estimation θ is the arg min of the following expression:

$$L_N(\boldsymbol{\theta}) = \frac{1}{2}\left(\hat{\boldsymbol{m}}_N - \boldsymbol{m}^S(\boldsymbol{\theta})\right)' \Omega^{-1} \left(\hat{\boldsymbol{m}}_N - \boldsymbol{m}^S(\boldsymbol{\theta})\right) \tag{43}$$

where,

$$\boldsymbol{m}^S(\boldsymbol{\theta}) = \begin{bmatrix} 2.40 & 3.05 & 3.50 & 4.44 & 0.081 & 0.049 & 0.032 & 0.016 & 0.10 & 0.72 \\ 2.41 & 2.98 & 3.41 & 4.34 & 0.086 & 0.050 & 0.037 & 0.019 & 0.34 & 0.67 \end{bmatrix} \tag{44}$$

$$\Omega^{-1} = \begin{bmatrix} 1 & 1 & 1 & 1 & 100 & 100 & 100 & 100 & 10 & 10 \\ 1 & 1 & 1 & 1 & 100 & 100 & 100 & 100 & 10 & 10 \end{bmatrix} \tag{45}$$

A.5 Simulated Moments

Table 6: **Data and Models Moments**

	Data	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Average Log Real Wages, Men, by wage percentiles							
0-25	2.398	2.234	2.222	2.223	2.203	2.197	2.174
25-50	3.053	2.717	2.709	2.708	2.703	2.721	2.722
50-75	3.498	3.313	3.304	3.294	3.293	3.307	3.331
75-100	4.441	4.691	4.673	4.634	4.627	4.597	4.680
Average Log Real Wages, Women, by wage percentiles							
0-25	2.408	2.191	2.251	2.292	2.394	2.489	2.581
25-50	2.978	2.605	2.652	2.674	2.762	2.846	2.926
50-75	3.410	3.136	3.172	3.176	3.253	3.318	3.398
75-100	4.338	4.400	4.416	4.378	4.436	4.445	4.540
Unemployment Rate, Men, by wage percentiles							
0-25	0.081	0.072	0.071	0.072	0.073	0.068	0.067
25-50	0.049	0.050	0.050	0.051	0.051	0.050	0.051
50-75	0.032	0.038	0.038	0.039	0.038	0.037	0.038
75-100	0.016	0.029	0.029	0.030	0.028	0.028	0.028
Unemployment Rate, Women, by wage percentiles							
0-25	0.086	0.076	0.074	0.075	0.075	0.069	0.067
25-50	0.050	0.066	0.065	0.067	0.067	0.066	0.066
50-75	0.037	0.045	0.044	0.046	0.046	0.047	0.049
75-100	0.019	0.032	0.032	0.033	0.032	0.032	0.033
Active Search, Men							
	0.720	0.848	0.831	0.830	0.816	0.794	0.768
Active Search, Women							
	0.672	0.684	0.671	0.672	0.655	0.603	0.561
Inactive Sample, Men							
	0.100	0.157	0.147	0.142	0.120	0.088	0.079
Inactive Sample, Women							
	0.342	0.208	0.234	0.258	0.295	0.311	0.375
Mean Square Error							
		0.892	0.750	0.633	0.489	0.418	0.596

Note: Averages of 100 simulations for each model with N=3000 individuals in simulated method of moments. Wages percentiles are by gender.

A.6 Descriptive Statistics: Children and job search

Table 7: **Children and job search behavior**

Dependent Variable: **Searching** *(Probability linear models regressions)*		
	CS sample	
Male	0.0852***	0.0375***
	(0.0065)	(0.0068)
Male * 1 child		0.0750***
		(0.0042)
Male * 2 children		0.0957***
		(0.0044)
Male * 3 or more children		0.0910***
		(0.0048)
1 child		-0.0324***
		(0.0027)
2 children		-0.0481***
		(0.0029)
3 children		-0.0515***
		(0.0032)
Constant	0.4731***	0.5010***
	(0.0123)	(0.0124)
Region FE	x	x
Quarter x Year FE	x	x
Age FE	x	x
Years of Education FE	x	x
Observations	787,832	787,832
Adjusted R-squared	0.155	0.157

Note: Individuals aged 18–65 without a job but willing and able to work right away. Source is PNADC 2012-22.