Sources of Gender Wage Gaps for Skilled Workers in Latin American Countries[*]

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Abstract

This paper identifies the impact of taste-based discrimination on labor market outcomes for nine Latin American countries. We use homogenized survey data on skilled workers to estimate a search and matching model of the labor market with explicit prejudice against women, participation decisions, and occupational choices. By gradually eliminating all potential sources of gender gaps, we find that prejudice is the only source that consistently impacts women, and plays a significant role in explaining gender wage gaps at the bottom of the wage distribution table. Additionally, prejudice has strong negative effects on gender gaps with respect to participation, employment/unemployment, and self-employment rates.

Keywords: Discrimination, Search Models, Structural Estimation, Latin America.

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1 Introduction

Gender gaps have remained elusively high in Latin America despite gender equality indicators having improved dramatically in the region in the past two decades. In most countries, women are under-represented in the labor market and receive much lower wages than men (Ortiz-Ospina, 2018). According to the *Global Gender Gap Report 2020* published by the World Economic Forum, progress has been made in closing educational, health, and political empowerment gender gaps in most countries, but gender labor market gaps remain sizable and persistent.

Since the 1950's, economists have extensively studied gender gaps and how these gaps may be linked to discriminating behavior (Becker, 1971). The literature on discrimination is vast and has focused on understanding why discrimination may arise, why it could persist, how it is measured, and what the individual and social consequences of such phenomena are.[1] Regarding Latin American countries, most of the literature evaluates gender wage gaps using a regression-based decomposition approach, to assess whether wage differentials were explained by individual characteristics or could be attributed to discrimination behavior.[2] Since workers anticipate that some employers discriminate against women in their decision making, discrimination affects not only wage gaps but also employment and participation gaps. Therefore, this literature has limitations in distinguishing the impact of discrimination from other unobserved gender-specific labor market characteristics, and evaluating policies against discrimination since the studies do not consider the equilibrium effects of policy on agents' decisions. Moreover, the literature for Latin American countries focus its attention

[1] Blau and Kahn (2017) and Olivetti and Petrongolo (2016) document long-term trends and provide insight into the factors driving these patters for the United States and other industrialized economies. Extensive literature reviews on methods to evaluate wage discrimination in the labor market can be found in Gunderson (2006), Altonji and Blank (1999), Blau (1998), Blau and Kahn (2000) and Neumark (2018).

[2] The methodologies used range from that proposed in the seminal papers written by Oaxaca (1973) and Blinder (1973), and later generalized by Oaxaca and Ransom (1994) and Neumark (1988), to more generalized approaches such as those suggested by Machado and Mata (2005), Melly (2005) and Nopo (2008). It is also worth mentioning that wage gaps that cannot be attributed to characteristics could be a result of inadequate data rather than discrimination.

mainly on evaluating wage gaps.[3]

In this paper we follow a different approach to analyze gender discrimination. In particular, we use a structural approach by developing a search and matching model of the labor market which defines gender discrimination as explicit prejudice against women (taste-based discrimination á la Becker, 1971). Our model extends the Flabbi (2010a) model by incorporating non-participation decisions as well as occupational choices. Notably, we include the possibility of self-employment, an occupational choice that is prevalent in low- and middle-income countries as an alternative for those who are not hired. We can hence identify the impact of prejudice simultaneously on wage gaps, occupational choices, and participation decisions. The advantage of this approach is that the decision-making process of workers and employers and all the unobservables are explicitly modeled, and the particular structure of the model can be used to identify these components in the data.[4]

We then estimate the model for nine Latin American countries (Argentina, Bolivia, Chile, Colombia, Ecuador, Mexico, Paraguay, Peru, and Uruguay), using cross-section data on participation, employment, wages, and unemployment duration for skilled workers, distinguishing between wage earners and self-employed workers. The identification strategy follows Flinn and Heckman (1982) for standard search models and Flabbi (2010a) for the specific parametrization of the discrimination component. The identification of this last component exploits the fact that, given the structure and the parametrization of the model, prejudice generates unique differences in the form of wage distributions for men and women.[5] We build three counterfactual scenarios to identify the relative impact of productivity differences, search frictions, and prejudice on wages, participation, and occupational segregation gender gaps. The counterfactual scenarios incorporate the fact that changes in the labor

[3]In developed countries the literature has explored not only gaps in varios outcomes of the labor market (Flabbi, 2010b, is an example), but also indirect effects of non labor market related decisions such as fertility decisiones (see Adda et al., 2017).

[4]The assessment of policies is less vulnerable to the Lucas critique, and it is possible to construct counterfactual scenarios (useful in analyzing the sources of the gap).

[5]We can identify differences in the forms because we perform a maximum likelihood estimation, and therefore we use information pertaining to the whole distribution

market environment induce individuals to adjust their behavior. Finally, we analyze the effect of a subsidy for hiring women and an equal-pay policy.

We find that, in Latin American countries, prejudice is the only source that consistently impacts women, and plays a significant role in explaining gender wage gaps among low wage earners. We also find that, in some countries, differences in productivity or labor dynamics, defined as transitions across labor market states, are important too. Our simulations assign prejudice a larger role for some countries (Chile, Argentina, Mexico), compared to others, such as Colombia, Peru, and Uruguay. In addition, prejudice has strong effects on gender gaps with regard to participation, employment/unemployment, and self-employment rates. When prejudice is neutralized, female self-employment rates drop, while both participation rates and employment rates rise. Finally, we find that a subsidy and an equal pay policy close gender gaps. Offering a relatively modest subsidy to hire women closes wage gaps in seven of the nine countries, while the equal-pay policy reduces not only wage gaps but also those in participation and self-employment in all nine countries.

We also construct an index of gender-related labor restrictions in the spirit of the one proposed by the World Bank (World Bank, 2020)[6] and show that our discrimination intensity estimates are strongly correlated with the amount and intensity of such labor restrictions. Chile and Mexico, for which our model estimates the highest intensity of discrimination, are also the two countries that rank the highest in our labor restriction index. Colombia, Paraguay, and Peru, on the contrary, have both low estimated discrimination intensity and low values in our index.

Our results are in line with the literature on developed countries analyzing gender wage differentials by structurally estimating a search model. For example, Sulis (2012) finds that labor dynamics are the main source of wage differentials in Italy, followed by productivity. This result is similar to our findings for half the countries in our study, for which labor dynamics is the first source of wage differentials (Bolivia, Colombia, Paraguay, and Peru).

[6] Our index includes a rich set of indicators and distinguishes between labor provisions that might either help or hinder women's position in the labor market.

In two countries, Chile and Mexico, labor dynamic differences favor women, in line with the results in Flabbi (2010a) for the Unites States. Also similar to Flabbi (2010a), we find that prejudice implies bigger differentials at the bottom of the wage distribution table. In these two countries, we also find Flabbi's pattern regarding the role of productivity differences: not hindering low-waged women, but being detrimental to moving up the wage distribution.[7] We add to this literature the introduction of self-employment, an aspect that is crucial if we want to understand gender differences in low- and middle-income countries. Lastly, a considerably literature has examined the determinants of gender wage gaps in Latin America (Nopo et al., 2010; Carrillo et al., 2014). This paper provides new insights by focusing also on other labor market outcomes.

The remainder of this paper is organized as follows. Section 2 describes the model. Section 3 describes the data and the estimation strategy. Section 4 presents and discusses the estimation results. Section 5 presents the results of our counterfactual experiments, while Section 6 presents the results of policy simulations. Finally, Section 7 concludes the study.

2 The Model

This section presents the theoretical model used to analyze the implications of different sources of gender wage gaps. In particular, we extend Flabbi (2010b)'s model to incorporate not only non-participation decisions but also occupational choices distinguishing wage earners and self-employed workers. Here, gender discrimination is defined as explicit prejudice against women in waged jobs and is therefore modeled as taste discrimination á la Becker (1971).

[7] Our model lacks some of the elements present in Bartolucci (2013), hence a comparison to his study is difficult. In particular, his study examines employee-employer match data and is able to explicitly estimate sector specific bargaining power parameters by gender.

2.1 Value Functions

The economy is populated by infinitely-lived risk-neutral agents, who discount time at rate ρ. There are two types of agents (men and women) indexed by $j = M, W$. At any point in time each agent can be non-participating in the labor market, unemployed, self-employed, or employed. Non-participating agents receive a flow utility z, which is drawn from the gender-specific distribution $Q_j(z)$, for devoting their time to activities other than those of the labor market. Since agents differ in how much they value their time outside of the labor market, only those with low enough utility z participate in it. In addition, differences in the distribution of z by gender capture the differences between men and women regarding the likelihood of participation. Defining the value of non-participation in the labor market for agent type j as NP_j, its flow value can be written as:

$$\rho NP_j(z) = z \tag{1}$$

An agent has an entrepreneurial ability y, which is drawn from the gender-specific distribution $R_j(y)$ and decides whether to search for a job or start a venture (that is, become self-employed). Differences in the distribution of y by gender incorporate the idea that women as entrepreneurs tend to operate on smaller scales and have lower productivity than their male counterparts (for empirical evidence on this issue see Sabarwal and Terrell, 2008).[8] Only unemployed individuals look for a job. Entrepreneurial ability is only known once the individual decides to enter the labor market. If the individual becomes self-employed, he/she receives y as flow income and remains in that state forever. Defining the value of self-employment as $S_j(y)$, the flow value of the self-employment state can be written as:

$$\rho S_j(y) = y. \tag{2}$$

[8]These differences could also reflect family constraints or other forms of discrimination, such as access to financial markets or consumer taste discrimination. In this paper we do not focus on trying to identify these other types of discrimination.

If the individual decides to look for a job, he/she becomes unemployed, receiving a flow utility b_j and meet a potential employer at Poisson rate λ_j while searching. Once the meeting occurs, a match-specific productivity x is drawn from a gender-specific productivity distribution $G_j(x)$.[9] We assume that the worker's entrepreneurial ability (y) and their potential match-specific productivity in a waged job (x) are independent. In the segment of high skilled workers, ventures and waged jobs have different technologies, different ability requirements, and perform different tasks (see for example Bradley, 2016; Bobba et al., 2020).

There are two types of employers in the economy, prejudiced and unprejudiced (indexed by $i = P, N$). Prejudiced employers receive a disutility when hiring a woman. There is a proportion p of this type of employers. An unprejudiced employer sees no difference in hiring a man or a woman. There is a proportion $1 - p$ of this type of employer. After meeting and observing the match-specific productivity, employers and employees engage in wage bargaining and decide whether to form the match or not. Let U_j and $V_{ji}(x)$ be the unemployment value and the value of being employed, respectively. The flow value of being unemployed for a type j agent is:

$$\rho U_j = b_j + \lambda_j \left\{ p \int \max\left\{V_{jP}(x) - U_j, 0\right\} dG_j(x) + (1-p) \int \max\left\{V_{jN}(x) - U_j, 0\right\} dG_j(x) \right\}. \tag{3}$$

When a type j worker is employed by a type i employer, in a match with productivity x, he/she receives a flow income equal to the wage rate $w_{ji}(x)$. Involuntary separation shocks arrive at a gender-specific Poisson rate η_j.[10] In case of termination, the worker starts to look

[9] For identification purposes we only assume that the distribution $G_j(x)$ belongs to the location-scale family of distributions. Aside from that, we do not make any other explicit assumptions about their behavior across gender and we leave the location and scale to be estimated using the data.

[10] Beccaria and Maurizio (2020) documents higher unconditional transition rates out of employment for women compared to men for six Latin American countries. However, conditioning on exits to unemployment, they also find that termination rates are not always higher for women and that there is considerable heterogeneity across countries. Additionally, Flabbi (2010a) finds higher transitions out of employment for women in the US labor market. To account for heterogeneous gender differentials in transition rates out of employment across countries, we allow for differences in termination rates by gender in our estimation.

for a new job as unemployed. The flow value of being employed is, therefore:

$$\rho V_{ji}(x) = w_{ji}(x) + \eta_j \left(U_j - V_{ji}(x)\right). \tag{4}$$

A prejudiced employer ($j = P$) receives a flow income equal to productivity x if a man is filling the vacancy, while it receives a flow income equal to $x - d$ if the worker in the match is a woman. Thus, parameter d represents the prejudiced employer's distaste for hiring a woman and is a measure of the intensity of discrimination. If the employer is unprejudiced ($i = N$), it receives a flow income equal to productivity x, regardless of the type of worker filling the vacancy. In turn, for a type i employer, the flow cost of having a vacancy filled by a type j worker with productivity x is the wage rate $w_{ij}(x)$. If an involuntary separation shock arrives, the match is terminated and the employer searches for a new worker to fill the vacancy. If $J_{ij}(x)$ is the value of a filled job, then the flow value is:

$$\rho J_{ji}(x) = x - dI_{W,P} - w_{ji}(x) - \eta_j J_{ji}(x), \tag{5}$$

where $I_{W,P}$ is an indicator variable equal to 1 if $j = W$ and $i = P$ and zero otherwise.

2.2 Wage Determination

Wages are determined by Nash bargaining, which splits the total surplus, $S_{ij}(x) = V_{ij}(x) - U_j + J_{ij}(x)$, into fixed proportions at all points in time. That is, the worker receives $V_{ij}(x) - U_j = \beta S_{ij}(x)$, while the employer receives $J_{ij}(x) = (1 - \beta) S_{ij}(x)$. Using these results, the wage equation is:

$$w_{ji}(x) = \rho U_j + \beta \left(x - dI_{W,P} - \rho U_j\right), \tag{6}$$

where β is interpreted as the bargaining power of the worker. Equation (6) indicates that the wage rate should at the very least guarantee the worker his/her outside option (the flow value of continuing to look for a job, ρU_j) plus a proportion β of the flow surplus of the match $x - dI_{W,P} - \rho U_j$ and the net of the utility cost d in the case of a women working for a prejudiced employer. The higher the β, the larger the portion of the surplus of the match captured by the worker.

Recent literature posits that women obtain a smaller share of the match surplus because they are less likely to initiate bargaining or they are less effective negotiators than men (see for example Card et al., 2015). However, given the unobservable nature of the surplus of the match, there is a fundamental identification problem regarding gender gaps in bargaining power, since it is not possible to separate low bargaining power from a worse match for women with respect to men without longitudinal or matched employer-employee data.[11] Bartolucci (2013), using a structural approach with matched employer-employee data for Germany, finds evidence of a lower bargaining power for women compared to men; however that difference is small and in some economic sectors is statistically not significant. In this paper, we are unable to identify the bargaining power parameter nor the potential wedge in this parameter between men and women because of data restrictions. Instead, as is common in the literature, we assume that $\beta = 0.5$, which characterizes a Nash equilibrium in a bargaining game with alternated offers and common discount rates for all workers and firms (Eckstein and van den Berg, 2007; Flabbi, 2010a).

2.3 Equilibrium and model implications

The equilibrium of the model consists of a set of reservation values related to the participation decisions given the utility z, of choosing an occupation (searching decision) given the entrepreneurial ability y, and of accepting a job with given productivity x. For the non-participation decision, the reservation value z_j^* makes the individual agent indifferent between participating or not in the labor market. That is, it satisfies $NP_j(z_j^*) = \int \max\{U_j, S_j(y)\}\, dR(y)$. Regarding the occupational choice, the reservation value y_j^* makes the worker indifferent between looking for a job or becoming self-employed and satisfies $\rho U_j =$

[11]This identification problem poses an additional challenge because the bargaining parameter itself is, in general, not identified without imposing additional structure on the model (Eckstein and van den Berg, 2007).

$\rho S_j(y^*)$. Using equations (1) and (2) leads to $y_j^* = \rho U_j$ and $z_j^* = \rho U_j R(\rho U_j) + \int_{\rho U_j} y dR_j(y)$. Thus, the decision is either to look for a wage job (as an unemployed individual) if $y \leq y^*$ or to otherwise start a venture as a self-employed individual. Meanwhile, any agent with $z \geq z^*$ does not participate in the market. Finally, in the case of a job acceptance decision, the reservation productivity x_{ji}^* satisfies $U_j = V_{ji}(x_{ji}^*)$. Using equations (4) and (6), reservation productivities for men are $x_{MP}^* = x_{MN}^* = \rho U_M$, while those for women, which depend on the type of employer, are $x_{WP}^* = \rho U_W + d$ and $x_{WN}^* = \rho U_W$. The reservation wages implied by these reservation productivities are $w_{MP}^* = w_{MN}^* = \rho U_M$ and $w_{WP}^* = w_{WN}^* = \rho U_W$. Finally, ρU_j is the solution of the Bellman equation:

$$\rho U_j = b_j + \frac{\lambda_j \beta}{\rho + \eta_j} \left\{ p \int_{\rho U_j + dI_W} [x - dI_W - \rho U_j] \, dG_j(x) + (1-p) \int_{\rho U_j} [x - \rho U_j] \, dG_j(x) \right\}. \tag{7}$$

The characterization of the equilibrium of the model is completed with the steady state conditions in the labor market. Defining the hazard rate arising out of unemployment as $h_j = \lambda_j[(1-p)(1 - G_j(\rho U_j) + p(1 - G_j(\rho U_j + dI_W))]$, for $j = M, W$, and normalizing the population by gender to 1 we have:

$$u_j = \frac{\eta_j}{h_j + \eta_j} R_j(y_j^*) Q_j(z_j^*) \tag{8}$$

$$e_j = \frac{h_j}{h_j + \eta_j} R_j(y_j^*) Q_j(z_j^*) \tag{9}$$

$$s_j = \left[1 - R_j(y_j^*)\right] Q_j(z_j^*) \tag{10}$$

$$np_j = 1 - Q_j(z_j^*) \tag{11}$$

where y_j^* and z_j^* are the reservation values defined above, u_j is the unemployment rate, s_j is the self-employment rate, e_j is the employment rate, and np_j is the non-participation rate.

The implication of the existence of prejudiced employers for the labor market outcomes are threefold. First, gender discrimination occurs by definition when two workers who are currently employed with identical productivity earn different wages. Regarding the model, the wage differentials between men and women working for prejudiced and unprejudiced employers are, respectively:

$$\begin{aligned} w_{WP}(x) - w_{MP}(x) &= (1-\beta)(\rho U_W - \rho U_M) - \beta d \\ w_{WN}(x) - w_{MN}(x) &= (1-\beta)(\rho U_W - \rho U_M) \end{aligned}$$

The direct impact of the existence of a prejudiced employer on wages is that the wage of women working for such employers is βd lower than that of other women. The indirect impact on wages, which we term the spillover effect, is an equilibrium effect, related to the fact that the flow value of unemployment is lower for women than for men, that is $\rho U_W < \rho U_M$ (see the proof of proposition 1 in Flabbi, 2010a). Consequently, wages are lower for women regardless of the type of employer because the presence of prejudiced employers worsens women's position in the bargaining process. This is the main mechanism in the model through which the existence of prejudiced employers affects the labor market.

Second, the spillover effect also affects the likelihood of forming a match of men and women by generating a wedge in the reservation wages by gender, again $w^*_{Wi} < w^*_{Mi}$. Importantly, even if the reservation wages of women are the same for different types of employers, the reservation productivities are not. Indeed, recall that $x^*_{WP} = \rho U_W + d$ while $x^*_{WN} = \rho U_W$, which implies that women are pickier if they end up matching with a prejudiced employer than with an unprejudiced employer (that is, the accepted productivity has to be higher to compensate for the penalty d). This generates partial segregation for women in the labor market because they tend to be over-represented with unprejudiced employers. Search frictions prevent total segregation in equilibrium because given an acceptable match-specific productivity $\tilde{x} > x^*_{WP}$, it is too costly for both women and prejudiced employers to go back and keep looking for another match (by definition $w_{WP}(\tilde{x}) > \rho U_W$ and $\tilde{x} - d - w_{WP}(\tilde{x}) > 0$).

Finally, the implications of the spillover effect go beyond the employment decisions and wage determination. Indeed, because ρU also represents the expected return of searching for a job, a lower return for women makes them less likely to participate; and if they do participate, it makes them more likely to become self-employed. Recall that the reservation values y_j^* and z_j^* depend on ρU_j, and therefore the existence of prejudiced employers have implications for the allocation of workers as it impacts their decisions regarding participation and becoming self-employed.

2.4 Model limitations

The model elucidated above allows us to analyze several aspects of the effect of taste discrimination, but it is highly stylized and thus has limitations. First, the model allows for the possibility of having equilibrium interactions among states in the labor market. However, it is limited with respect to the direction of those interactions. In particular, since there are no dynamics in participation decisions and occupational choices (they are made only once), the labor market information is available only when the worker decides to participate, and the match specific-productivity distribution does not depend on worker characteristics other than gender. Heterogeneity, regarding non-market value and entrepreneurial ability, has no implications on employment and wage determination. We are aware that this limits the range of questions that can be answered with this particular model. For example, we can analyze the effect of changes in the wage policy or in the hiring decisions on different margins of the labor market outcomes, but we cannot analyze other relevant questions such as the impact of policies that encourage participation or the effect of the number of times (and the duration) women are outside the labor market regarding wages and employment.

In making the assumptions of no dynamics in non-participation decisions and occupational choices we face a trade-off. To identify the primitive parameters in a model with dynamics on those margins, a panel data structure is required–in particular, data on transitions across labor market states. This type of data is not available for the majority of countries in the study sample. Since we aim to analyze a wide group of Latin American countries, we are limited to using cross-sectional data with its consequent implications on the assumptions of the model.

Second, the model does not allow for forms of discrimination other than taste-based discrimination. The main example would be statistical discrimination. In the model, employers observe a worker's productivity at the moment of the match and decide to hire by comparing that productivity with the reservation rule; in the case of statistical discrimination, the productivity is not observed and therefore employers have to decide to hire based on their pre-existing beliefs regarding average productivity by gender. Another example would be discrimination via differentiated jobs postings for jobs that can be equally performed by men or women. Here, we would observe differences in the rates of job availability for men and women for reasons that differ from pure search frictions. The reason for ignoring other forms of discrimination, like statistical discrimination, is since identification of numerous discrimination sources, differences in productivity, and search frictions simultaneously would be impossible based on observable variables of the labor market alone.

3 Data and Estimation

3.1 Data

We use data from both household and employment surveys conducted in nine Latin American countries for the period 2013—2015. Table 1 provides a detailed description of the data and their sources. Not all surveys have the same periodicity. For example, in Chile, they are conducted every two years; Bolivia and Uruguay have annual surveys; Colombia conducts monthly surveys; Ecuador, Mexico, Paraguay, and Peru have quarterly surveys. The data on labor status, wages, and working hours are comparable, since all the surveys follow a similar questionnaire pattern and enquire about weekly working hours and monthly wages in the month prior to the survey. To avoid the potential influence of seasonality in our data, we use surveys for the last quarter, except for Bolivia and Colombia. For the former, we collapse two years to record more observations on unemployed individuals. For the latter, we use the December survey since the wages and working hours data collected correspond to November, the middle data point for the last quarter. The data are homogenized to recover information on wages, gender, (ongoing) unemployment duration, age, education, and employment status.[12]

All data sets are representative at the national level. To guarantee a certain degree of homogeneity consistent with the model, the analysis focuses on men and women between 25 and 55 years of age who have either a tertiary (technical) or university degree. Data on wages are obtained from the individual's primary occupation only, and hourly wages are estimated using reported working hours for this occupation and are expressed in constant PPP US dollars as of December 2013.[13]

Table 2 presents descriptive statistics by country and gender. Several observations emerge. First, in some countries, there is a higher proportion of women than that of men in our sample of highly skilled workers. This is not surprising as advances in the education of women in Latin America have been extensively documented in the literature (Duryea et al., 2007). Second, much heterogeneity exists across countries with respect to labor outcome levels as well as gender gaps. Colombia has higher unemployment and self-employment rates for both women and men, as well as the highest gaps in unemployment rates between women and men (along with Ecuador and Peru). For most countries in the sample, gaps in participation rates range from 7% to 13%, except in Mexico where the gap is 28%. The lowest participation rate for women is found in Mexico (67%), which is significantly below those observed in the other countries (82%—91%). The highest unemployment durations for women are found in Bolivia, Paraguay, and Uruguay. The highest raw wage gaps are found in Chile and Ecuador, where women earn 28% and 19% less than men, respectively. In Chile, women's wages have the highest relative dispersion. In all sample countries, wage distributions for men show a

[12] Details on the data homogenizing process are provided in the online appendix A.

[13] Note that our model does not distinguish between formal and informal wage earners. Therefore, the sample of wage earners includes both categories. It is preferable to include informal workers in our analysis, since the segmentation of labor markets is likely to be incomplete between these two sectors in Latin America. Moreover, for the type of workers we are considering, those with tertiary education or higher, the informality rate among wage earners is at most 12% (see Table 2 in the online appendix A).

higher relative dispersion than those for women.

3.2 Estimation method

The model is estimated by maximum likelihood methods using cross-section information on the supply side of the labor market for each country. An advantage of the estimation procedure and the strategy for identifying the sources of gender gaps described in Flabbi (2010a) is that the data requirements are not particularly stringent, a feature that is relevant when analyzing most Latin American countries. In particular, the data used include the labor market status of individuals (indicator variables for inactivity, self-employment, unemployment, and employment), unemployment (outgoing) durations t_k observed for unemployed agents[14] and hourly wages w_k observed for employees, by gender.

The non-participation information–an indicator variable that identifies whether the individual is not participating in the labor market–contributes to the likelihood function through the probability of not participating in the labor market. In the model this probability is denoted by:

$$\Pr[k \in NP|j] = 1 - Q_j(z_j^*), \tag{12}$$

where z_j^* is the reservation value of the participation decision. In turn, the contribution of self-employment information (an indicator variable that equals one when individual is self-employed and otherwise zero), to the likelihood function is the joint probability of observing an individual participating and being self-employed. In the model, this probability is:

$$\Pr[k \in S, k \in P|j] = \Pr[k \in S|k \in P, j] \Pr[k \in P|j] = [1 - R_j(\rho U_j)] Q_j(z_j^*). \tag{13}$$

Regarding duration data, its contribution to the likelihood function is the density function

[14] With ongoing unemployment duration data, all observations are right censored by definition. However, this does not generate a bias problem in our context because, under the constant hazard rate property of the model, the downward bias generated by incomplete spells is canceled out with the upward bias generated by a low probability of observing very short durations. Consequently, the density function of the ongoing durations is equivalent to the density function of complete durations (see Flinn and Heckman, 1982, 1983).

of unemployment duration for such only observed for individuals who are participating and unemployed. That is,

$$
\begin{aligned}
f_t(t_k, k \in U, k \in P|j) &= f_t(t_s|k \in U, k \in P, j)\,\Pr[s \in U|k \in P, j]\,\Pr[s \in P|j] \\
&= h_j e^{-h_j t_k}\left[\frac{\eta_j}{h_j+\eta_j} R_j\left(\rho U_j\right)\right] Q_j(z_j^*),
\end{aligned} \tag{14}
$$

where h_j is the hazard rate arising out of unemployment defined in 2.3.[15]

Finally, the contribution to the likelihood of wage data assumes that observed wages are accepted and observed only for those individuals participating in the labor market and the employed. The construction of the density of observed wages involves three steps. First, the productivity distribution $g_j(x)$ is mapped into the wage distribution through the wage equation in (6). Second, the resulting wages distribution is truncated to the range of accepted wages, which is all wages greater than the reservation wage. Third, the joint probability of observing those accepted wages and being employed is calculated. The resulting contributions are

$$
\begin{aligned}
f^o_{ei}(w_k, w > \rho U_j, k \in U, k \in P|j) &= f_{ji}(w_k|w > \rho U_j, k \in U, k \in P, j)\,\Pr[k \in E|k \in P, j]\,\Pr[k \in P|j] \\
&= \frac{\frac{p}{\beta} g_j\left(\frac{w_k+\beta dI_{W,P}-(1-\beta)\rho U_j}{\beta}\right)}{1-G_j(\rho U_j + dI_{W,P})}\left[\frac{h_j}{\eta_j+h_j} R_j\left(\rho U_j\right)\right] Q_j(z_j^*),
\end{aligned} \tag{15}
$$

for $i = N, P$. Because the type of employer is not observed, $f^o_{eN}(\cdot)$ contributes with probability $1-p$ and $f^o_{eP}(\cdot)$ contributes with probability p.

The parametric assumptions regarding the distribution of the three sources of heterogeneity in the model complete the description of the likelihood function. First, we assume

[15] The unemployment durations have a negative exponential distribution, which is a direct consequence of a constant hazard rate, conditional on the model (Eckstein and van den Berg, 2007). In the case of Argentina, where the structure of the duration data is defined as intervals, the contribution of the duration data uses $\left[1-e^{-h_j t_k^{(2)}}\right]-\left[1+e^{-h_j t_k^{(1)}}\right]$, for the interval of durations $t_k^{(2)}-t_k^{(1)}$, instead of the negative exponential density function.

that the value of out-of-the-labor-market activities z and the entrepreneurial ability y follow a negative exponential distribution. That is, $Q_j(z) = 1 - e^{-\gamma_j z}$ and $R_j(y) = 1 - e^{-\theta_j y}$, respectively.[16] Finally, for the match-specific productivity x, we use a log-normal distribution with a density function, $g_j(x) = \frac{1}{\sigma_j x}\phi\left(\frac{\ln(x)-\mu_j}{\sigma_j}\right)$, where $\phi(\cdot)$ is the normal standard density function.

By combining equations (12) to (15), the log-likelihood function to be maximized on choosing the set of parameters Θ is:

$$
\begin{aligned}
&\ln L(w,t,U,E,S,NP;\Theta) = \qquad\qquad (16)\\
&\sum_{j=M,W}\left\{\sum_{k=1}^{N_{j,NP}} \ln \Pr[k \in NP|j] + \sum_{k=1}^{N_{j,S}} \ln \Pr[k \in S, k \in P|j] + \sum_{k=1}^{N_{j,U}} \ln f_t(t_k, k \in U, k \in P|j) + \right.\\
&\left.\sum_{k=1}^{N_{j,E}} \ln\left((1-p)f^o_{eN}(w_k, w > \rho U_j, k \in U, k \in P|j) + p f^o_{eP}(w_k, w > \rho U_j, k \in U, k \in P|j)\right)\right\},
\end{aligned}
$$

where $\Theta = \{\lambda_M, \lambda_W, \eta_M, \eta_W, \mu_M, \sigma_M, \mu_W, \sigma_W, p, d, \rho U_M, \rho U_W, \gamma_M, \gamma_W, \theta_M, \theta_W\}$.

3.3 Identification

The identification argument is as follows.[17] Using the results in Flinn and Heckman (1982), the reservation wage ($\rho\hat{U}_j$) can be estimated using the minimum observed wage in the sample of employed workers.[18] Additionally, under the assumption of a negative exponential distribution for y, the reservation wage and the proportion of individuals who are self-employed provide sufficient information to estimate the parameter θ_j. Similarly, $\rho\hat{U}_j$, $\hat{\theta}_j$ and the proportion of non-participating individuals provide sufficient information to estimate parameter γ_j, once again under the assumption of a negative exponential distribution for z.

[16] We do not attempt to fit the distribution of self-employment earnings because information on those earnings is typically very noisy in Latin American countries. Instead, we use only self-employment rate information. This imposes a restriction on the number of parameters of the distribution $R_j(y)$ that we can identify, i.e. we can only fit a one-parameter distribution.

[17] For a detailed discussion on identification see Flabbi (2010a).

[18] Following Flabbi (2010a), we drop 2.5% of the lowest observations when estimating the reservation wage.

Given $\rho\hat{U}_j$, $\hat{\theta}_j$, and $\hat{\gamma}_j$ for $j = M, W$, a concentrated version of the likelihood function presented in equation (16) can only be estimated over the following parameters $\Theta' = \{\lambda_M, \lambda_W, \eta_M, \eta_W, \mu_M, \sigma_M, \mu_W, \sigma_W, p, d\}$. As discussed in Flabbi (2010a), the rate at which workers and potential employers meet (λ_j) is identified from the unemployment duration data, while both λ_j and the steady state condition are necessary to identify the arrival rate of termination shocks.[19] In turn, productivity distributions are identified from the observed wage distributions using the productivity to wages mapping and the truncation point at the reservation productivity. The invertibility feature of the log-normal distribution makes this identification possible as the original distribution can be recovered from a truncated distribution (Flinn and Heckman, 1982).

The two key parameters, p and d, can be identified by exploiting differences between the productivity distributions of men and women. The necessary condition for identifying p and d, in addition to the parameters of the productivity distributions, is that those distributions belong to a location-scale family.[20] Under this family of distributions, parameters p and d distort the shape of the implied wage distribution of the model (a mixture of distributions by gender), particularly in the slope of the lower tail of the distribution (Flabbi, 2010a). The log-normal satisfies this condition.

Finally, as is commonplace in the literature that estimates structural search models with supply side data, we do not attempt to identify the parameter β–the bargaining power of workers in the Nash bargaining game. Instead we follow the literature and set its value at 0.5 (Eckstein and van den Berg, 2007).[21] Additionally, parameters ρ and b are not separately

[19] In a steady state, the flows in and out of unemployment should be equal to consistently maintain the number of unemployed and employed workers.

[20] A location-scale family is a family of probability distributions parametrized by two parameters, a location parameter and a (non-negative) scale parameter. The former determines the position or the shift of the distribution, while the latter determines how much the distribution is spread out.

[21] Given the discussion in subsection 2.2 regarding the context of gender gaps, we perform a robustness exercise to assess the impact of gender gaps in the bargaining power on our estimates. In particular, we estimate the model for any combination of (β_M, β_W), such that $\beta_M \geq \beta_W$, in an interval constructed with 15% above and below 0.5. This generates a maximum differential of 35% between β_M and β_W. We find that the impact of generating an edge between the bargaining parameters by gender does not appear to generate estimates that would change the overall results of the paper. In fact, the biggest dispersion generated by the wedge in β is 28%. See online appendix B for details.

identified because both affect the reservation values. To identify b, we set ρ and use the equilibrium condition and the estimates for the reservation wages. The values of ρ for each country are borrowed from Lopez (2008).

4 Estimation Results

Table 3 presents the estimated parameters. Rows (1) and (2) indicate the estimates of the monthly Poisson rate at which workers meet potential employers. There is considerable heterogeneity among the countries regarding how often job offers arrive, but no pattern can be found by gender. Job offers arrive after an average period that ranges from 1 to 8.5 months in the case of men, with Peru and Argentina (closely followed by Uruguay) being the countries with the highest and the lowest job offer frequency, respectively. In the case of women, job offers arrive after an average period ranging from 0.94 to 13.5 months, with Peru and Argentina also being the extreme cases. In Argentina, Bolivia, and Paraguay, job offers arrive at a much slower rate for women than for men, while in Colombia, Ecuador, and Uruguay the frequency gap is far smaller, although still favorable for men. In the remaining three countries, job offers arrive faster for women than for men.

The estimates of the Poisson rate at which involuntary separation shocks occur, which convey information on the average duration of a job, are shown in rows (3) and (4). As in the case of the arrival rate of jobs, average job duration displays considerable heterogeneity in Latin America. Argentina, Bolivia, Ecuador, Paraguay, and Uruguay are the countries where job durations are longer, regardless of gender. In these countries, jobs last for between 11 and 22 years for men and between 8 and 33 years for women. In contrast, in Colombia, Mexico, and Peru, jobs last for at most 3 years, on average. In Bolivia and Paraguay, the job duration for women is very high relative to men (60%-100% higher), while job duration for men is almost double that for women in Colombia and Peru. In Chile, Mexico, and Uruguay, gender differences are smaller.

The model provides estimates for the location and the scale parameters of the productivity distributions by gender (rows (5) to (8)). Given the log-normality assumption, the average productivity implied in these estimates is indicated by gender in the second row of the top and middle panels of Table 4 labeled $E[x]$.[22] In five of the nine countries, average productivity is higher for men than for women, with greater differences observed in Chile and Ecuador (36% and 20%, respectively). In Colombia, Paraguay, and Peru, productivity gaps between men and women (although in men's favor) are smaller (4% to 7%). In the remaining four countries, women are more productive than men, by 4% to 6% in Bolivia and Mexico, but by almost 10% in Argentina and Uruguay.

Rows (9) and (10) of Table 3 show the estimates of the intensity of discrimination and the proportion of prejudiced employers. Two comments are worth mentioning before discussing the results. First, according to the likelihood ratio test (LR), found in the last row of the table, the null hypothesis of there being no prejudiced employers in the economy ($p = 0$) and no disutility of hiring a woman ($d = 0$) is rejected for all countries, except Colombia. Second, the intensity of discrimination is not directly comparable across countries and skill levels because workers have different productivities in both dimensions. To compare the results, a relative measure of the intensity of discrimination is defined as the ratio between parameter d and the average productivity of men, $E[x|M]$.

The relative measures of the discrimination section of Table 3 shows the measure of relative intensity (d^R) and the proportion of total workers whose employer is prejudiced (p^R). Two main facts emerge. First, the intensity of discrimination ranges between 13% and 41% of the average productivity for men. The lowest intensity of discrimination is found in Colombia and Ecuador, while the highest is found in Chile and Mexico (around 40%). The intensity of discrimination is around 25% to 30% in Argentina, Uruguay, and Bolivia, and around 15% in Paraguay and Peru. Second, countries in our sample are similar in the proportion of prejudiced employers. The country with the lowest proportion is Peru (38%), while the

[22] Recall that if $x \sim LogNormal(\mu, \sigma)$ then $E[x] = e^{\mu+0.5\sigma^2}$ and $V[x] = (e^{\sigma^2} - 1)e^{2\mu+\sigma^2}$.

highest rate is observed in Paraguay (almost 43%).

Rows (11) and (12) show the estimates of the reservation wages by gender. In all countries, except for Bolivia, men's reservation wage tends to be higher than women's (from 5% to 22%), which implies that employers are pickier when hiring a woman. The largest difference is found in Peru and Colombia, followed by Ecuador, Chile, and Uruguay. In Argentina, Bolivia, and Paraguay, women's reservation wages are marginally different from men's (+/- 2%). The estimated parameters of distributions $Q(z)$ and $R(y)$ are presented in rows thirteen to sixteen of the table.

Regarding the goodness of fit of the model, Table 4 presents the model predictions for several measures. Comparing these predictions with the descriptive statistics presented in Table 2, it is noted that the overall fit of the model is very good for all countries.

5 Counterfactual Experiments

5.1 Experiments

To analyze the effect of each potential source on gender gaps, we perform a set of counterfactual experiments. In each experiment, one potential source of the gender wage gap is turned off, and the ratio of wages between women and men is calculated for the average and for the top and bottom 25% of the wage distribution. We also compute gaps in the proportion of individuals in the unemployment, employment, and self-employment states and in the participation rate. Since we compute the resulting equilibrium in the model for each counterfactual scenario, we can separate, while considering changes in agents' decisions, the individual effect of gender differences in productivity, the arrival rate of jobs, and the discrimination intensity. While we can analyze the individual impact of these three sources of gender gaps, we cannot disentangle all of the mechanisms behind each of them.[23] Regardless of this limitation, we

[23]Gender differences in termination rates, arrival rates or productivity could reflect differences in search strategies or the ability of networking, among other factors. We are unable to identify the mechanism behind each result. We only model the effect of prejudice on wages and employment decisions.

discuss the relationship between some gender institutions in Latin American countries and the intensity of discrimination estimated with the model in the next subsection.

In the first experiment (called Productivity) we analyze the importance of productivity differences by equalizing the productivity distributions between women and men (by setting the point estimates of μ and σ for women to those of men). All the remaining parameters are set at their point estimates. In the second experiment (called Prejudice) we analyze the role of discrimination intensity and the proportion of prejudiced employers in gender gaps. In this experiment, we set d and p to zero. Finally, in the third experiment (called Transitions) we analyze the role of gender differences in labor market dynamics. Here, we set the arrival rates of jobs and involuntary separations of women to the point estimates for men.

The gap (women's outcome relative to men's) that each experiment generates[24] is presented in Table 5. Additionally, for comparison purposes, the gap predicted by the model, with all parameters set at their point estimates, is presented as Baseline. Column (1) presents the mean wage gap, while columns (2) and (3) present wage gaps at the bottom and top 25% of the wage distribution. Columns (4) to (7) present the predicted gaps in all states of the labor market.

In the absence of differences in productivity between men and women, countries can be divided into two groups. The first is composed of Argentina, Bolivia, Mexico, and Uruguay, where women are more productive than men. In this group, turning off productivity differences make women worse off such that relative participation and employment rates would fall, while self-employment rates would increase. On average, wage ratios would drop, implying that wage gaps would increase. The impact on wage gaps is also positive and stronger for low wage earners, but negative (5—10 pp) for high wage earners. In the second group, composed of Chile, Colombia, Ecuador, Paraguay, and Peru, where women are less productive than men in the benchmark, equalizing productivity differences pushes up participation and employment rates (while also increasing unemployment rates) and reduces women's self-

[24] Recall that the wage gap is the wages of women as a fraction of that of men. Therefore, a wage gap of 0.89 implies that the model predicts that women on average earn 11% less than men.

employment rates. Average wage ratios would increase and, in all countries except for Chile, higher gains would be found at the top 25% of the distribution. This effect is more pronounced in Paraguay and Peru, and less so in Ecuador and Colombia. In Chile, on the contrary, wage gaps increase predominantly for low wage earners.

Under no prejudice, women are better off in all countries. Gender gaps in participation rates and women's self-employment rates are lower. In all countries, except Chile, higher relative participation rates in this scenario correspond to higher relative unemployment rates for women, but relative employment rates increase in all cases. Average wage ratios are higher (wage gaps are reduced) and, in Argentina, Bolivia, Mexico, and Uruguay, average wage ratios become favorable for women (see Table 5). In all countries, a stronger effect is found for low wage earners. Three countries stand out regarding the relative importance of prejudice: Chile, Mexico, and Uruguay. In Chile, under no prejudice, the wage gap shrinks from 30% to 10% (although it remains favorable for men). At the bottom 25%, gaps become favorable to women, who in turn earn 40% more than men. For low wage earners gains are smaller, with an initial gap of almost 35% which shrinks to 25% when prejudice is turned off. In Mexico and Uruguay, where wage gaps are smaller (7% and 8%, respectively), prejudice is also an important source of wage differentials such that when prejudice is turned off, wage gaps become favorable to women on average (wage ratios are 1.16 and 1.08, respectively) and for the bottom 25% (1.54 and 1.38, respectively). At the top, the wage gap between women and men vanishes in Mexico and improves from 0.86 to 0.93 in Uruguay. In Uruguay, wage gaps are small, but prejudice plays an important role despite this.

In five countries (Argentina, Bolivia, Colombia, Paraguay, and Peru), labor market dynamics are a very important source of gender wage differentials. Labor market dynamics hinder women in these countries. Hence, if they are neutralized, relative participation and employment rates increase, while self-employment rates decrease. Wage ratios would also improve, on average and on the top, but predominantly for low wage earners. In fact, average wage ratios become favorable for women in this scenario in these countries. On the contrary, in Chile and Mexico, labor market transitions favor women and turning off differences in labor market dynamics reduces participation rates and employment rates, while increasing self-employment. Wage gaps grow by almost 10 percentage points on average, increasing by up to 30 percentage points for low wage earners. In Ecuador and Uruguay, labor market transitions play a minor role.

In conclusion, wage gap levels vary widely by country and in terms of the relative importance of their sources: productivity, prejudice, and labor market dynamics. Prejudice is a major source of wage gaps in all countries. If we turn prejudice off, wage ratios increase in all countries. Prejudice matters the most for low wage earners, yet it also generates sizable wage gaps at the top of the distribution. Colombia is the only country in the sample where the data are not consistent with the existence of prejudice. There is no clear pattern regarding the relative importance of productivity and labor market dynamics. In countries where women are on average more productive (Argentina, Bolivia, Mexico, and Uruguay), turning off productivity differences increases wage gaps overall, and particularly for low wage earners. Labor market dynamics favor skilled women in only two of the nine countries (Chile and Mexico), play a minor role in Uruguay, and hinder women in the remaining six countries. Once again, larger effects are found at the bottom of the distribution.

5.2 Discussion: Pro-women legislation and gender discrimination

We estimate a model in which the existence of prejudiced employers generates large gender gaps in wages and other labor market outcomes. As explained in subsection 2.3, the existence of prejudiced employers has both a direct and an equilibrium effect. Prejudiced employers penalize women by offering them lower wages and increasing the match-specific threshold for hiring them. Conversely, the presence of prejudiced employers lowers women's outside options, regardless of the employer type. Women are more likely, then, to remain out of the labor force or become self-employed.

In Latin America, there is widespread legislation that protects women's rights in the labor market. Generally, this legislation abides by International Labor Organization (ILO) guidelines concerning maternity protection and women's rights. We construct an index (hereafter "pro-women index") for women's labor rights in the spirit of the *Women, Business and the Law* (World Bank, 2020) but distinguishing between labor provisions that might either help or hinder women's position in the labor market. A detailed description on the construction of our index can be found in online appendix C.[25]

Table 6 shows that there is a clear ranking. The countries with the highest pro-women index are Chile, Bolivia, and Mexico, while those with the lowest index are Colombia and Paraguay, followed by Peru and Uruguay. It is also relevant to consider the coverage of pro-women's policies. Uruguay and Chile have the highest coverage, while Paraguay has the lowest. Chile has the highest pro-women index and the highest coverage, while Paraguay lies at the opposite end, with low protection and low coverage. There is no clear pattern for the other sample countries. This is an important issue to note, as low coverage may reduce the effectiveness of the protection legislation.

Our pro-women index is highly correlated with the discrimination intensity measure estimated by the model. Chile and Mexico have the highest estimated discrimination intensity. At the other end are countries such as Ecuador, Peru, and Paraguay, for which our model predicts the lowest discrimination intensity measure in the sample. Accordingly, based on the index, Ecuador has standard maternity policies in place, but has one of the lowest effective coverage rates, as estimated by the ILO. In contrast, Paraguay and Peru systematically rank lowest in our pro-women index. These countries rank low on the index as they only protect women from dismissal during pregnancy and maternity leave (90 days), a very short period compared to that offered in the other sample countries (9—18 months). Colombia, where the existence of discrimination is rejected by our model has the lowest relative protection index among our sample. It is also one of the countries (the other being Peru) that have enacted (by law) an equal pay policy that is subject to reporting requirements.

[25] In the online appendix we also provide a comprehensive review of maternity legislation for all the countries in our sample, and a detailed description on constructing the index.

One possible hypothesis for this positive correlation is the presence of prejudiced employers and the existence of d in countries may have specific labor market policies that could introduce uncertainty in hiring women, which in turn generates utility costs for some employers. IN such a scenario, a fraction p of employers would offer lower wages to women; the stronger the laws that discriminate in favor of women, the higher the gender gap in wage offers (d). Another possible hypothesis is that the presence of prejudiced employers, with potentially higher discrimination intensity d, lead the countries to respond by passing stronger laws against discrimination. If we observe high gender gaps due to discrimination and strengthen laws that favor women, it could indicate that those laws are not effective in closing those gender gaps. However, our model does not allow us to distinguish the direction of the causality.

6 Policy experiments

We use the model to analyze the potential impact of two different labor market policies aimed at mitigating gender gaps: a subsidy to hire a woman and an equal-pay policy.[26] In the first case, a subsidy is offered to all employers. In the second, a law is passed, obliging all employers to pay equal wages to women and men. In both cases, we measure the impact of the policy on workers' welfare and other labor market outcomes such as wages, unemployment duration, and labor market participation, among others.[27] Results are presented in Table 7. Panel A, labeled "Base Model," presents the benchmark scenario, with no policy. The first three rows present welfare measures for both women and men and for the whole sample. The last six rows present gaps in reservation wages, unemployment, self-employment and participation rates, unemployment duration, and average wages. As expected, women achieve a lower welfare level than men. Chile, Peru, Colombia, and Ecuador (in this order) have the largest

[26] Alternative policies evaluated in recent literature are gender based taxation in favor of women as in Alesina et al. (2011), or affirmative action in the form of quotas as in Moro and Norman (2003).

[27] We use the welfare measure proposed by Flinn (2002) to evaluate the impact of the policy experiments on welfare. See details in online Appendix D.

welfare gaps between men and women.

Panel B, labeled "Hiring Subsidy," posits a scenario in which employers are encouraged to hire women by offering a subsidy of 10% of d (discrimination intensity). The subsidy is financed by taxing the labor income of all workers (the tax rate is the value needed to balance the government budget in equilibrium). We observe that welfare falls for men (maximum 4% in Mexico), and increases for women (from 3% in Paraguay and Ecuador to 11% in Chile). Welfare is reduced for men, as they now receive a smaller after-tax salary. Regarding labor market outcomes, the policy closes the gap in two countries and reverts it in favor of women in five countries. The largest effects are found in Mexico and Chile, where discrimination intensity is the highest.[28] In Argentina, Bolivia, and Uruguay, this policy increases wage ratios from 0.93—0.95 to 1.13—1.18. The effects on participation rates, unemployment rates, and unemployment duration are more modest. In all the countries, women's reservation wages increase relative to men's, while relative self-employment rates see a decline.

Panel C, labeled "Equal Pay Policy," posits a scenario where all employers are forced to pay both women and men the same wage at equal productivity. The wage rate is then defined as a weighted average of the bargained wages of women and men in the benchmark scenario. As this policy neutralizes wage gaps for men and women who have equal productivity, differences in average wages are due to differences in the average productivity in both groups. In this scenario, men's welfare drops more than that with the hiring subsidy. The smallest impact is observed in Colombia (2 percentage points), while the largest impacts are observed in Mexico and Chile (24 and 29 percentage points, respectively). Women, obviously, benefit from the policy, with their welfare gain ranging from 1 percentage point in Colombia to 13 percentage points in Mexico. Wage gaps improve after the policy with the largest reduction in Mexico (13 percentage points) and the smallest in Colombia (3 percentage points). In Argentina, Bolivia, Chile, and Uruguay, the impact on wages is also high (8 to 11 percentage points). In all these countries, except Chile, wage gaps in this scenario are favorable for

[28]Note how the policy also closes gaps in employment and participation and reduces self-employment rates.

women (6% in Argentina, 3% in Bolivia and Uruguay). This policy does affect reservation wages, unemployment, participation, and self-employment rates in all countries, but stronger effects are found in Mexico and Chile. The policy generates a convergence in participation rates but reduces relative self-employment rates and increases (relative) unemployment for women.

In conclusion, both policies generate convergence in wages and labor force participation. Both policies reduce relative self-employment rates but slightly increase the relative unemployment rates of women. Regarding our measure of welfare, the hiring subsidy dominates the equal-pay policy. This occurs because the men's wage drop that is necessary to equalize wages in the equal-pay policy is higher than the men's wage loss due to the tax used to finance the subsidy. Note, however, that from an administrative point of view, the "hiring subsidy" is easier to implement via the tax system and might have more immediate effects. In contrast, "Equal Pay Policies" are harder to implement because productivity is observed only imperfectly. In addition, they are unlikely to be successful unless governments are willing to invest in technologies or protocols to monitor progress and to impose sanctions to not-abiding employers.

7 Final Remarks

This paper estimates a search model of the labor market with taste-based discrimination, participation decisions, occupational choice, and match-specific heterogeneity for nine Latin American countries. The model allows us to separate the impact of prejudice from the influence of other gender-specific labor market characteristics, such as unobserved productivity and gender differences in labor market dynamics. In all the countries examined the model accurately replicates the average gender wage gaps as well as those observed at the top and bottom of the wage distribution in the sample countries.

The existence of prejudiced employers in the model generates wage gaps between men and women (direct effect) and lowers women's outside option (the spillover effect); regardless of the employer type, women are less likely to participate in the labor market and more likely to be self-employed. The spillover effect is the main mechanism in the model through which the existence of prejudiced employers affects the labor market. Indeed, by reducing women's present value of looking for a job in equilibrium, discrimination in the model not only affects wage determination (bargaining), but also the reservation values on various margins of decisions (employment, occupational choice and participation). Our estimations and simulations indicate that prejudice is the only source that consistently hurts women, particularly among low wage earners. In many countries, productivity differences are also important, and its main impact is concentrated among high wage earners.

Policy simulations of a hiring subsidy and an equal-pay policy indicate that the most effective policy is to subsidize women's hiring. The exceptions are Chile and Mexico, where discrimination intensity is the highest, and the equal-pay policy has stronger effects, closing gaps in unemployment and participation and reducing women's self-employment rates. It should be noted that a policy's ease of implementation as well as is effectiveness should be considered. A hiring subsidy administrated via the tax system has the additional advantage of being easier to establish than an effective equal-pay policy.

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Table 1: Data Sources

Country	Code	Survey Name	Survey Code	Years	Wave
Argentina	ARG	Encuesta Anual de Hogares Urbanos	EAHU	2014	-
Bolivia	BOL	Encuesta de Hogares	EH	2013/2015	-
Chile	CHL	Encuesta de Caracterización Socieconómica Nacional	CASEN	2103	-
Colombia	COL	Gran Encuesta Integrada de Hogares	GEIH	2015	December
Ecuador	ECU	Encuesta de Empleo, Desempleo y Subempleo	ENEMBU	2014	4th Quarter
Mexico	MEX	Encuesta Nacional de Ocupación y Empleo	ENOE	2014	4th Quarter
Paraguay	PAR	Encuesta Permanente de Hogares	EPH	2013/2014	4th Quarter
Peru	PER	Encuesta Nacional de Hogares sobre Condiciones de Vida y Pobreza	ENAHO	2013	4th Quarter
Uruguay	URU	Encuesta Continua de Hogares	ECH	2014	-

Table 2: Descriptive Statistics

	ARG	BOL	CHI	COL	ECU	MEX	PAR	PER	URU
					Women				
N_W	4013	1867	8190	3895	3096	16675	2380	4354	8137
N_W/N	0.63	0.49	0.55	0.60	0.58	0.60	0.60	0.53	0.61
$Pr(U)$	0.03	0.02	0.05	0.12	0.03	0.04	0.02	0.04	0.03
$Pr(E)$	0.74	0.64	0.71	0.51	0.74	0.53	0.78	0.63	0.73
$Pr(S)$	0.11	0.15	0.08	0.23	0.09	0.10	0.10	0.17	0.15
$Pr(P)$	0.88	0.82	0.84	0.86	0.87	0.67	0.90	0.84	0.91
$E(w\|E)$	12.15	6.75	11.06	6.16	7.58	6.89	8.60	6.80	9.57
$SD(w\|E)$	5.58	3.79	8.69	4.35	3.96	4.22	4.53	4.79	5.59
$E(t\|U)$	-	12.11	3.04	4.86	4.46	2.97	10.03	0.96	7.69
$SD(t\|U)$	-	11.79	3.92	6.13	3.98	3.60	8.10	0.89	6.32
					Women/Men				
$Pr(U)$	1.41	1.12	1.17	1.66	1.60	0.90	1.18	1.69	1.27
$Pr(E)$	1.06	1.01	1.04	1.00	1.07	1.06	1.04	0.98	1.07
$Pr(S)$	0.69	0.95	0.71	0.83	0.61	0.81	0.74	0.97	0.75
$Pr(P)$	0.91	0.87	0.88	0.89	0.89	0.72	0.93	0.87	0.93
$E(w\|E)$	0.96	0.94	0.72	0.90	0.81	0.93	0.87	0.88	0.93
$SD(w\|E)$	0.84	0.75	0.67	0.91	0.65	0.86	0.71	0.81	0.72
$E(t\|U)$	-	2.26	1.03	1.02	1.12	0.97	1.78	0.95	1.05
$SD(t\|U)$	-	2.02	1.08	1.10	1.01	0.96	1.45	0.65	0.94

NOTE: N_W is the number of women in the sample, N_W/N is the proportion of women in the total sample, $Pr(U)$ is the proportion of unemployed workers in the sample, $Pr(E)$ is the proportion of employed workers in the sample, $Pr(S)$ is the proportion of self-employed workers in the sample, $Pr(P)$ is the participation rate, $E(w|E)$ and $SD(w|E)$ are, respectively, the average and the standard deviation of wages observed only for employed workers. Finally, $E(t|U)$ and $SD(t|U)$ are the average and the standard deviation of the unemployment duration, respectively. In the case of Argentina the duration data is defined in intervals.

Table 3: Estimated Parameters

	ARG	BOL	CHL	COL	ECU	MEX	PAR	PER	URU
λ_M	0.118	0.188	0.345	0.228	0.254	0.328	0.180	1.000	0.137
	(0.0001)	(0.028)	(0.029)	(0.016)	(0.001)	(0.0003)	(0.0004)	(0.092)	(0.013)
λ_W	0.074	0.086	0.425	0.213	0.229	0.371	0.103	1.059	0.133
	(0.0000)	(0.014)	(0.009)	(0.010)	(0.003)	(0.0002)	(0.0004)	(0.079)	(0.009)
η_M	0.004	0.006	0.021	0.031	0.008	0.029	0.004	0.042	0.004
	(0.0000)	(0.001)	(0.001)	(0.003)	(0.0001)	(0.0000)	(0.0000)	(0.006)	(0.001)
η_W	0.003	0.003	0.023	0.050	0.010	0.025	0.003	0.076	0.005
	(0.0000)	(0.001)	(0.0001)	(0.003)	(0.0002)	(0.0000)	(0.0000)	(0.009)	(0.001)
μ_M	2.898	2.286	2.938	2.013	2.515	2.318	2.587	2.310	2.639
	(0.008)	(0.019)	(0.077)	(0.031)	(0.007)	(0.001)	(0.001)	(0.015)	(0.012)
σ_M	0.594	0.704	0.854	0.887	0.699	0.723	0.688	0.756	0.712
	(0.007)	(0.015)	(0.041)	(0.024)	(0.053)	(0.0002)	(0.012)	(0.012)	(0.009)
μ_W	3.058	2.433	2.742	2.014	2.446	2.454	2.597	2.353	2.788
	(0.002)	(0.090)	(0.026)	(0.021)	(0.051)	(0.001)	(0.003)	(0.064)	(0.036)
σ_W	0.439	0.538	0.717	0.808	0.550	0.581	0.538	0.640	0.538
	(0.002)	(0.042)	(0.094)	(0.017)	(0.023)	(0.001)	(0.004)	(0.032)	(0.017)
d	6.080	3.680	11.115	0.000	2.000	5.204	2.915	1.917	4.261
	(0.002)	(1.806)	(0.318)	(0.0000)	(0.053)	(0.004)	(0.020)	(1.891)	(0.874)
p	0.499	0.499	0.496	0.536	0.500	0.498	0.500	0.500	0.499
	(0.086)	(0.374)	(0.952)	(0.0000)	(0.507)	(0.030)	(0.295)	(0.672)	(0.181)
w^*_M	3.646	1.751	3.205	2.102	2.741	1.724	2.812	1.828	2.353
w^*_W	3.593	1.774	2.959	1.700	2.506	1.674	2.793	1.422	2.177
θ_M	0.466	0.922	0.640	0.532	0.630	0.966	0.663	0.864	0.633
θ_W	0.575	0.941	0.812	0.768	0.885	1.124	0.773	1.133	0.814
γ_M	0.899	1.431	0.904	1.227	1.303	1.424	1.155	1.560	1.441
γ_W	0.560	0.872	0.591	0.945	0.772	0.614	0.791	1.139	1.005
Relative Measures of Discrimination:									
d^R	0.281	0.292	0.409	0.0000	0.127	0.395	0.173	0.143	0.236
p^R	0.409	0.390	0.416	0.3150	0.414	0.384	0.424	0.377	0.390
Fixed Parameters:									
β	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
ρ	0.062	0.094	0.067	0.053	0.094	0.056	0.094	0.067	0.062
N	4862	2663	11471	4037	4119	17433	3125	5755	9878
lnL	-15195	-7315	-39289	-12009	-11660	-50164	-9039	-16067	-30488
LR	82	18	24	0	6	142	9	15	97

NOTE: Asymptotic standard errors in parentheses. The relative measure of discrimination are: $p^R = p\Pr[E]$ and $d^R = d/E[x|M]$

Table 4: Model Predictions

	ARG	BOL	CHL	COL	ECU	MEX	PAR	PER	URU
					Women				
$E(y)$	1.79	1.15	1.69	1.06	1.30	1.63	1.26	0.88	1.00
$E(x)$	23.43	13.16	20.06	10.38	13.42	13.78	15.51	12.90	18.78
$SD(x)$	10.81	7.63	16.43	9.97	7.98	8.73	8.98	9.17	10.87
$E(w)$	12.00	6.55	8.75	6.04	7.46	6.43	8.42	6.68	9.42
$E(w\|E)$	12.14	6.76	11.03	6.20	7.58	6.91	8.59	6.78	9.57
$E(t\|U)$	13.71	12.11	3.04	4.86	4.46	2.97	10.03	0.96	7.69
$Pr(U)$	0.03	0.02	0.05	0.12	0.03	0.04	0.02	0.05	0.03
$Pr(E)$	0.74	0.64	0.71	0.50	0.74	0.53	0.78	0.63	0.73
$Pr(S)$	0.11	0.15	0.08	0.23	0.09	0.10	0.10	0.17	0.15
$Pr(P)$	0.88	0.82	0.84	0.86	0.87	0.67	0.90	0.84	0.91
					Women / Men				
$E(y)$	1.60	1.64	1.53	1.30	1.69	2.32	1.46	1.37	1.43
$E(x)$	1.08	1.04	0.74	0.94	0.85	1.05	0.92	0.96	1.04
$SD(x)$	0.77	0.76	0.58	0.82	0.64	0.80	0.69	0.78	0.74
$E(w)$	0.95	0.91	0.58	0.92	0.81	0.86	0.86	0.88	0.92
$E(w\|E)$	0.96	0.94	0.71	0.89	0.81	0.92	0.87	0.88	0.93
$E(t\|U)$	1.61	2.26	1.03	1.02	1.12	0.97	1.78	0.95	1.05
$Pr(U)$	1.28	0.98	1.03	1.47	1.42	0.65	1.10	1.47	1.18
$Pr(E)$	0.96	0.88	0.91	0.89	0.95	0.76	0.97	0.86	0.99
$Pr(S)$	0.63	0.83	0.62	0.74	0.54	0.58	0.69	0.84	0.70
$Pr(P)$	0.91	0.87	0.88	0.89	0.89	0.72	0.93	0.87	0.93

NOTE: Model predictions are based on the estimates reported in Table 3. $E(y)$ is the average self-employment income due to an entrepreneurial ability y, $E(x)$ and $SD(x)$ are, respectively, the average and the standard deviation of the match-specific productivity, $E(w)$ is the average wage, $E(w|E)$ is the average wage for those who are employed (accepted wages), $E(t|U)$ is the average unemployment duration, $Pr(U)$ is the proportion of unemployed workers, $Pr(E)$ is the proportion of employed workers, $Pr(S)$ is the proportion of self-employed workers, and $Pr(P)$ is the participation rate.

Table 5: Counter-factual Experiments

Country	Closing Differences in:	Wages Average	Wages P25	Wages P75	Labor Market States $Pr(U)$	$Pr(E)$	$Pr(S)$	$Pr(P)$
ARG	Baseline	0.96	1.02	0.89	1.28	0.96	0.63	0.91
	Productivity	0.89	0.78	0.94	1.20	0.86	0.85	0.87
	Prejudice	1.11	1.36	0.97	1.42	1.08	0.35	0.96
	Transitions	1.10	1.35	0.96	1.27	1.19	0.13	1.00
BOL	Baseline	0.94	1.02	0.87	0.98	0.88	0.83	0.87
	Productivity	0.93	0.85	0.97	0.98	0.83	0.93	0.85
	Prejudice	1.07	1.36	0.94	1.11	1.04	0.53	0.94
	Transitions	1.18	1.69	0.99	1.48	1.27	0.09	1.04
CHL	Baseline	0.71	0.81	0.67	1.03	0.91	0.62	0.88
	Productivity	1.37	1.97	1.22	1.61	1.17	0.01	1.04
	Prejudice	0.90	1.39	0.75	1.13	1.16	0.06	1.02
	Transitions	0.61	0.49	0.62	0.47	0.39	2.20	0.63
COL	Baseline	0.89	0.89	0.86	1.47	0.89	0.74	0.89
	Productivity	1.00	0.99	1.00	1.73	1.00	0.57	0.92
	Prejudice	0.89	0.89	0.86	1.47	0.89	0.74	0.89
	Transitions	1.04	1.28	0.94	1.37	1.30	0.31	0.98
ECU	Baseline	0.81	0.92	0.74	1.42	0.95	0.54	0.89
	Productivity	1.06	1.15	1.03	1.80	1.11	0.19	0.97
	Prejudice	0.88	1.08	0.78	1.53	1.03	0.36	0.93
	Transitions	0.86	1.03	0.76	1.10	1.07	0.31	0.94
MEX	Baseline	0.92	0.94	0.88	0.65	0.76	0.58	0.72
	Productivity	0.91	0.77	0.96	0.57	0.64	0.76	0.66
	Prejudice	1.16	1.54	0.99	0.91	1.15	0.11	0.94
	Transitions	0.82	0.64	0.83	0.27	0.26	1.49	0.49
PAR	Baseline	0.87	0.98	0.79	1.10	0.97	0.69	0.93
	Productivity	1.00	1.01	1.00	1.24	1.04	0.49	0.96
	Prejudice	0.95	1.17	0.84	1.15	1.04	0.49	0.96
	Transitions	1.03	1.39	0.87	1.29	1.17	0.12	1.01
PER	Baseline	0.88	0.91	0.84	1.47	0.86	0.84	0.87
	Productivity	0.97	0.94	0.99	1.77	0.99	0.56	0.93
	Prejudice	0.99	1.17	0.90	1.83	1.08	0.40	0.96
	Transitions	1.04	1.33	0.92	1.33	1.24	0.14	1.01
URU	Baseline	0.93	1.02	0.86	1.18	0.99	0.70	0.93
	Productivity	0.91	0.79	0.96	1.11	0.90	0.89	0.90
	Prejudice	1.08	1.38	0.93	1.37	1.17	0.32	0.98
	Transitions	0.95	1.07	0.87	1.08	1.06	0.57	0.95

NOTE: The table reports the ratio W/M. The baseline is the benchmark wherein all potential sources of gender gaps are included. In each experiment we close one source of gender gaps. The experiment *Productivity* equalizes the match-specific productivity distribution between men and women, the experiment *Prejudice* eliminates prejudice employers from the labor market ($p = 0$ and $d = 0$), and finally, the experiment *Transitions* equalizes the arrival rates of jobs and the termination rates between men and women. All counterfactual experiments are based on the estimates reported in Table 3.

Table 6: Pro-Women Index vs Relative Discrimination

	Pro-women Index			Effective coverage		Relative discrimination	
	Total Index	Index Without employer's costs	Ranking	Index	Ranking	Index	Ranking
Argentina	0.35	0.43	5	0.36	6	0.28	4
Bolivia	0.73	0.66	2	0.36	5	0.29	3
Chile	0.80	1.00	1	1.00	1	0.41	1
Colombia	0.21	0.27	9	0.73	3	-	-
Ecuador	0.40	0.47	4	0.10	9	0.13	8
Mexico	0.42	0.50	3	0.36	8	0.39	2
Paraguay	0.26	0.32	8	0.36	7	0.17	6
Peru	0.29	0.36	7	0.73	4	0.14	7
Uruguay	0.31	0.39	6	1.00	2	0.24	5

NOTE: The Pro-women Index is estimated using data from the ILO Working Conditions Laws Database (ILO, 2019). Effective coverage is taken from Addati et al. (2014).

Table 7: Policy Experiments

	ARG	BOL	CHL	COL	ECU	MEX	PAR	PER	URU
Panel A: Base Model									
Welfare Measures									
Men	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Women	0.94	0.90	0.59	0.76	0.79	0.88	0.86	0.70	0.91
Total	0.96	0.95	0.77	0.86	0.88	0.93	0.92	0.84	0.94
Labor Market Variables (Women/Men)									
w^*	0.99	1.01	0.92	0.81	0.91	0.97	0.99	0.78	0.93
$Pr(U)$	1.28	0.98	1.03	1.47	1.42	0.65	1.10	1.47	1.18
$Pr(S)$	0.63	0.83	0.62	0.74	0.54	0.58	0.69	0.84	0.70
$Pr(P)$	0.91	0.87	0.88	0.89	0.89	0.72	0.93	0.87	0.93
$E(t\|U)$	1.61	2.26	1.03	1.02	1.12	0.97	1.78	0.95	1.05
$E(w\|E)$	0.96	0.94	0.71	0.89	0.81	0.92	0.87	0.88	0.93
Panel B: Subsidy of Hiring a Woman									
Welfare Measures									
Men	0.99	0.99	0.96	1.00	1.00	0.95	1.00	0.98	0.99
Women	0.98	0.94	0.66	0.76	0.81	0.95	0.89	0.72	0.95
Total	0.98	0.97	0.79	0.86	0.89	0.95	0.93	0.85	0.96
Labor Market Variables (Women/Men)									
w^*	1.06	1.10	1.17	0.81	0.95	1.19	1.04	0.86	1.02
$Pr(U)$	1.32	1.03	1.15	1.47	1.44	0.74	1.11	1.55	1.23
$Pr(S)$	0.56	0.74	0.39	0.74	0.50	0.43	0.64	0.74	0.61
$Pr(P)$	0.91	0.89	0.92	0.89	0.89	0.76	0.94	0.89	0.94
$E(t\|U)$	1.61	2.25	1.02	1.02	1.11	0.96	1.78	0.95	1.04
$E(w\|E)$	1.18	1.18	1.08	0.89	0.91	1.26	1.01	1.01	1.13
Panel C: Equal Pay Policy									
Welfare Measures									
Men	0.88	0.88	0.72	0.97	0.94	0.76	0.93	0.89	0.87
Women	1.00	0.99	0.70	0.77	0.83	1.01	0.90	0.78	0.99
Total	0.95	0.93	0.71	0.85	0.87	0.91	0.91	0.83	0.94
Labor Market Variables (Women/Men)									
w^*	1.29	1.36	1.93	0.87	1.08	1.87	1.16	1.13	1.31
$Pr(U)$	1.43	1.12	1.37	1.53	1.51	0.93	1.15	1.81	1.37
$Pr(S)$	0.41	0.55	0.17	0.68	0.41	0.24	0.52	0.50	0.42
$Pr(P)$	0.94	0.92	1.01	0.90	0.91	0.84	0.95	0.93	0.96
$E(t\|U)$	1.57	2.16	0.92	1.01	1.10	0.90	1.74	0.94	1.02
$E(w\|E)$	1.07	1.03	0.80	0.91	0.86	1.05	0.92	0.96	1.03

NOTE: All welfare measures are relative to those of men in the base model. w^* is the reservation wage, $Pr(U)$ is the proportion of unemployed workers, $Pr(S)$ is the proportion of self-employed workers, $Pr(P)$ is the participation rate, $E(t|U)$ is the unemployment duration and $E(w|E)$ is the average wage for those who are employed (accepted wages). All policy experiments are based on the estimates reported in Table 3.