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

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Abstract

We estimate a search model of the labor market with participation decisions, occupational choice, and gender prejudice for skilled workers in nine Latin American countries. We separate the impact of prejudice from the influence of other gender-specific labor market characteristics, such as productivity and labor market dynamics. We find that prejudice is an important source of gender gaps, but not necessarily the main force. Prejudice plays a larger role in explaining gender wage gaps among low-wage earners, while productivity differences are the main source for high wage earners. We rationalize the presence of prejudiced employers by the existence of labor market policies that increase the cost of hiring women. Some employers, with high aversion to cost uncertainty, discount women wages. We also analyze the effects of a hiring subsidy and an equal-pay policy. If employers are offered a relatively modest subsidy (10% of the wage penalty), the gender wage gaps can be closed in most countries.

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

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1 Introduction

Most Latin American countries have grown considerably in the last 10 years, mainly due to the particularly positive cycle of commodity prices in the world. However, they are still behind in reducing income inequality and other economic disparities, such as gender and racial gaps. Latin America is by far one of the regions with the lowest female labor force participation rates. Women are not only under-represented in the labor market, but also receive, on average, much lower wages than men. According to the *Global Gender Gap Report 2014* published by the World Economic Forum, there has been good progress in closing educational, health and political empowerment gender gaps in most countries, but gender labor market gaps are still sizable and persistent in time. Consequently, the region fell to the fourth place in the ranking when labor market gaps were considered and to the fifth place (out of six) when labor force participation and wage gaps were used separately.

There is a vast literature that have focused on assessing whether observables and unobservables explain wage gaps in the region, using either the traditional Blinder-Oaxaca decomposition technique[1] or more generalized approaches such as those suggested by Machado and Mata (2005), Melly (2005) and Nopo (2008).[2] Nopo et al. (2010), using data from eighteen countries, find substantial inter-country heterogeneity both in the raw gaps and in the unexplained gender gaps. Raw hourly wage gaps can be as high as 20% (Peru), but as low as 0.5% (Argentina). In most countries, in terms of observable characteristics, women are better than men, but there is evidence of strong sorting into low-pay occupations. After controlling for differences in women and men characteristics, wage gaps (unexplained portion) can be as high as 20%. However, as pointed out in the literature, all these approaches can be useful for describing wage gaps but they cannot solve the fundamental identification problem; that is, how can the impact of discrimination be separated from other gender-specific labor market

[1] Oaxaca (1973) and Blinder (1973)), subsequently generalized by Oaxaca and Ransom (1994) and Neumark (1988).

[2] Most papers use years of education, age, type of worker (salaried or non-salaried) and occupation as observables.

characteristics (such as unobserved productivity). Since workers, when making labor market decisions, anticipate that some employers discriminate against women, discrimination not only affects wage gaps but also participation and segregation gaps.

In this paper, we follow the strategy developed by Flabbi (2010a) to identify explicit gender discrimination in the labor market in nine Latin American countries: Argentina, Bolivia, Chile, Colombia, Ecuador, Mexico, Paraguay, Peru and Uruguay. The theoretical model extends the Flabbi (2010b) search and matching model by incorporating not only non-participation decisions but also occupational choices. Even though the model is highly stylized, it is rich enough in its dynamics to consider the various potential gender gap sources. Gender discrimination is defined as explicit prejudice against women, modeled as taste (disutility) discrimination a la Becker (1971). We structurally estimate the model using data on participation, wages, and unemployment duration for skilled workers, distinguishing between wage earners and independent workers. Identification conditions follow results in Flinn and Heckman (1982) for standard search models and those in Flabbi (2010a) for specific parametrization of the model's discrimination component. We build three counter-factual scenarios to identify the relative impact of productivity differences, search frictions, and prejudice on wage, participation and occupational segregation gender gaps. The decomposition incorporates the fact that changes in the labor market environment induce individuals to adjust their behavior. Finally, we analyze the effect of a subsidy for hiring women and an equal pay policy.

To apply this structural approach, we use a cross-section database for each country with supply side information obtained from the countrys' Household Surveys. To our knowledge, this is the first paper that estimates gender gaps using a structural approach for Latin American countries and from a cross-country perspective. In this approach the decision-making process of workers and employers and all the unobservables are explicitly modeled, and the particular structure of the model is used to identify these components in the data.[3]

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

We find that, in Latin American countries, prejudice is an important source of gender gaps, but not necessarily the main force. Both differences in labor dynamics and productivity are also important when explaining gender gaps. In fact, prejudice plays a larger role in explaining gender wage gaps among low-wage earners. Prejudice also has strong effects on gender gaps in participation, employment/unemployment and self-employment rates. When prejudice is neutralized, women's self-employment rates drop, while both participation rates and employment rates rise. We rationalize the existence of discrimination as having employers who are more averse to the cost uncertainty that pro-women policies may create. We construct a pro-women index and show that our discrimination intensity estimates are quite well aligned with the amount and intensity of such provisions. On one end, we have Chile and Mexico, for which our model estimates the highest intensity of discrimination. These two countries also rank the highest in our pro-women index. On the other end we have Colombia, Paraguay and Peru, with low estimated discrimination intensity and low pro-women index.

Our results are in contrast to those in the literature for Latin America (Nopo et al., 2010), in the sense that although we find that prejudice plays an important role in explaining wage gaps, in some countries differences in productivity or labor dynamics are also as important. For some countries (Chile, Argentina, Mexico) our simulations assign a larger role to prejudice, while for others, such as Colombia, Peru and Uruguay, we find that prejudice plays a minor role in explaining gender wage differentials. In simulating the effects of a hiring subsidy and an equal-pay policy, we find that if we were to offer employers a relatively modest subsidy (10% of wage penalty), we could close gender wage gaps in most countries.

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 decomposition of the sources of gender gaps, while Section 6 presents the results of the policy simulations. Finally, section 7 concludes.

2 The Model

For the structural analysis we follow Flabbi (2010a) strategy to identify explicit gender discrimination. This section presents the theoretical model used to decompose gender wage gaps into their sources. We use an extended version of Flabbi (2010b) model that incorporates non-participation decisions, as well as occupational choices. In this setting, gender discrimination is defined as explicit prejudice against women and modeled as taste discrimination á la Becker (1971).[4]

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 $j = M, W$. 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 a draw from the gender-specific distribution $Q_j(z)$, from 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 will be participating in it.[5] 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 individual has an entrepreneurial ability y, which is a draw 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). Only unemployed individuals search for a job. Entrepreneurial ability is only known once the individual decides to enter the market. While searching for a job, unemployed individuals receive a flow utility b_j and meet a potential employer at Poisson

[4] Hereafter, we will interchange throughout the text the terms discrimination and prejudice.

[5] Also, differences in the distribution of z by gender capture the differences between men and women's likelihood of participating.

rate λ_j. Once the meeting occurs, a match-specific productivity x is drawn from a gender specific productivity distribution $G_j(x)$. There are two types of employers in the economy: prejudiced or unprejudiced (indexed by $i = P, N$). Prejudiced employers receive a disutility when meeting and hiring a woman. There is a proportion p of this type of employers. For an unprejudiced employer, hiring a man or a woman makes no difference. There is a proportion $1 - p$ of this type of employers. After meeting and fulfilling 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:

$$\rho U_j = b_j + \lambda_j \left\{ p \int \max\left\{V_{jP}(x) - U_j, 0\right\} dG_j(x) + (1-p) \int \max\left\{V_{jN}(x) - U_j, 0\right\} dG_j(x) \right\} \tag{2}$$

A self-employed individual receives y as flow income and stays 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:

$$\rho S_j(y) = y \tag{3}$$

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 gender specific Poisson rate η_j. In case of termination, the worker starts to look 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 job, while he/she receives a flow income equal to $x - d$ if the 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 discrimination intensity. If the employer is unprejudiced

($i = N$), he/she receives a flow income equal to productivity x, regardless of the type of worker filling the job. 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:

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

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

2.2 Wage Determination

Finally, 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:

$$w_{ji}(x) = \beta\left(x - dI_{[j=W,i=P]}\right) + (1-\beta)\rho U_j \tag{6}$$

where β is interpreted as the bargaining power of the worker. Equation (6) indicates that workers are paid a weighted average, according to their bargaining power, of the productivity, which discounts the disutility of hiring a woman for a prejudiced employer, and their outside option (that is, the unemployment flow value). The presence of parameter d in wage equation (6) shows the direct effect of taste discrimination on wages.

2.3 Equilibrium

The equilibrium of the model consists of a set of reservation values related to the decisions of participating given the utility z, of choosing an occupation (searching decision) given the entrepreneurial ability y, and of accepting a job 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 $NP_j(z_j^*) = \int \max\{U_j, S_j(y)\} R(y)dy$. In the case of the occupational choice, the reservation value y_j^* satisfies $\rho U_j = \rho S_j(y^*)$. Using equations (1) and (3) leads to $y_j^* = \rho U_j$ and $z_j^* = \rho U_j R(\rho U_j) + \int_{\rho U_j} y r_j(y)dy$. Thus, the decision is either to search for a wage job (as unemployed) if $y \leq y^*$ or to start a venture as self-employed, meanwhile any agent with $z \geq z^*$ will not participate in the market. Finally, in the case of the job accepting 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 $w_{WP}^* = w_{WN}^* = \rho U_W$.

To conclude the description of the model, we present the steady state equilibrium in the labor market. Normalizing the population by gender to 1 we have:

$$u_j = \frac{\eta_j}{h_j + \eta_j} \frac{R(y_j^*)}{1 - Q_j(z_j^*)} \tag{7}$$

$$e_j = \frac{h_j}{h_j + \eta_j} \frac{R(y_j^*)}{1 - Q_j(z_j^*)} \tag{8}$$

$$s_j = 1 - R(y_j^*) \tag{9}$$

$$np_j = Q_j(z_j^*) \tag{10}$$

where 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.

2.4 Empirical Implications of the Model

The presence of prejudiced employers in the model economy has direct and indirect impacts on labor market outcomes and affects multiple margins of decisions. There are two direct effects. The first occurs on wages since prejudiced employers "discount" from wages the disutility received from hiring a woman. The second is a penalty on the requirements of hiring since prejudiced employers are particularly pickier than unprejudiced employers when hiring a woman. The larger the parameter d is the higher the match-specific productivity requirements x for hiring. Additionally, because women searching for a job do not know ex-ante the type of employer they will meet, the higher productivity requirements for prejudiced employers reduce the likelihood of forming a match, resulting in a higher unemployment duration.

The indirect effect is a general equilibrium effect. Flabbi (2010a), in Proposition 1, show that in equilibrium $\rho U_W < \rho U_M$; therefore, the outside option of women in the wage bargaining process is lower, regardless of the type of employer. This result, called the spillover effect, indicates that the presence of prejudiced employers worsens women's position in the labor market even when dealing with an unprejudiced employer. In this model, the implications of this result goes beyond the employment decision and wages determination. Indeed, because ρU represents the expected return of searching for a job, a lower return, with respect to the case without prejudiced employers, makes women less likely to participate; and if they do participate, they are more likely to become self-employed (recall that reservation values y_j^* and z_j^* depend on ρU_j). The implications of these last results on the allocation of workers is relevant since women with lower value of non-market activities will remain out of the labor market and women with lower entrepreneurial ability will become self-employed.

Even though the model allows for the possibility of having equilibrium interactions among states in the labor market, it has limitation in terms of the direction of those interactions. In particular, since there are no dynamics in participation decisions and occupational choices (they are made once), the labor market information is available only when the worker decides to participate, and the match specific-productivity distribution does not depend on the characteristics of the worker other than gender, heterogeneity, in terms of non-market value and entrepreneurial ability, has no implications on employment and wages 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 also relevant questions like the impact policies that encourage participation or the effect of how many times (and how long) women are outside the labor market on 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 that we analyze. Since we aimed 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. As we mentioned above, the constrained model does not eliminate the possibility of having equilibrium interactions among states in the labor market.

3 Data and Estimation

3.1 Data

In this paper, we use data from both household and employment surveys conducted in nine Latin American countries. The data is homogenized to recover information on wages, gender, (ongoing) unemployment duration, age, education, and employment status. More information about the data homogenizing process is provided in the online appendix A.

All data sets are representative at the national level. The analysis focuses on men and women between 25 and 55 years old who have either a tertiary (technical) or university degree. Data on wages are obtained from the individuals' primary occupation only, and hourly wages are estimated using reported working hours for this occupation, expressed in constant PPP US dollars of December 2013.[6] The reasons for for focusing our attention

[6] Not all the surveys have the same periodicity since they are conducted every two years (Chile), annually (Bolivia and Uruguay), every month (Colombia), or quarterly (Ecuador, Mexico, Paraguay and Peru). In any case, when asking questions about wages and hours of work, all the surveys followed a similar questionnaire in

on wage differentials among wage earners only is that it is difficult to rationalize the idea of discrimination or prejudice in a self-employment context.[7] In eight out of nine countries in our sample, self-employed workers represent, on average, less than 20% of the skilled employment. The exception is Colombia, where this figure is 30%. Self-employment is a valid employment state in the model, but it does not distinguish between formal and informal workers among the wage earners. It is not appealing to leave informal workers out from our analysis, since the segmentation of labor markets is likely to be incomplete between these two sectors in Latin America.

Table 1 presents descriptive statistics by country and gender. There is a huge inter-country heterogeneity in unemployment duration and unemployment rates. Countries like Chile, Mexico, and Peru display the shortest (ongoing) unemployment duration, while Uruguay, Bolivia, and Paraguay have the longest. Unemployment duration is higher for women, except in Mexico and Peru, where this relationship is reversed. The largest gaps in unemployment duration by gender is found in Bolivia and Paraguay, while the smallest gaps are observed in Chile, Colombia, and Uruguay. The highest unemployment rates are found in Colombia, Mexico, and Chile, while the largest gaps (in men's favor) are in Peru and Argentina. Mexico is the only country where women's unemployment rates are lower than men's. In turn, the largest gender wage gap is found in Chile (followed by Ecuador), while the smallest gaps are seen in Uruguay, Bolivia, and Mexico. In all countries, except for Colombia, men's wage distributions show a higher relative dispersion than women's. Chile displays the highest relative wage dispersion for both women and men.

which they ask about hours of work and wages in the previous month. In order to avoid the potential influence of seasonality in our data, we always work with data collected in the last quarter, with the exception of Bolivia and Colombia. For Bolivia, we pool two years, in order to have more observations on the unemployed. For Colombia, we use the December survey, since information on wages and hours of work in this survey correspond to November, the middle data point for the last quarter.

[7]Note also that even if we were interested in studying gender income differentials among self-employed workers, self reported data on income for self-employed workers are typically very noisy and affected by measurement errors.

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 data requirements are not particularly stringent, a feature that is relevant when analyzing the case of most Latin American countries. In particular, the data used includes labor market status of individuals (indicator variables for inactivity, self-employment, unemployment and employment), unemployment (outgoing) durations t_s observed for unemployed agents[8] and hourly wages w_s observed for workers, by gender.

The non-participation information, that is an indicator variable that identifies whether the individual is not participating in the labor market, contributes to the likelihood function throughout the probability of not participating in the labor market. Conditional on the model, that probability is:

$$\Pr[s \in NP|j] = 1 - Q_j(z_j^*) \tag{11}$$

where z_j^* is the reservation value of the participation decision. In turn, the contribution of self-employment information, an indicator variable that identifies whether the individual is self-employed and zero otherwise, to the likelihood function is the joint probability of observing an individual participating and being self-employed. Conditional on the model, that probability is:

$$\Pr[s \in S, s \in P|j] = [1 - R_j(\rho U_j)]\, Q_j(z_j^*) \tag{12}$$

In the case of duration data, its contribution to the likelihood function is the probability density function of unemployment durations considering that those durations are observed

[8] 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 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. As a result, the density function of the ongoing durations is equivalent to the density function of complete durations (see Flinn and Heckman, 1982, 1983).

only for individuals who are participating and unemployed, that is

$$\begin{aligned} f_t(t_s, s \in U, s \in P|j) &= f_t(t_s|j) \Pr[s \in U|j] \Pr[s \in P|j] \\ &= h_j e^{-h_j t_s} \left[\frac{\eta_j}{h_j + \eta_j} R_j \left(\rho U_j \right) \right] Q_j(z_j^*) \end{aligned} \tag{13}$$

where h_j is the hazard rate out of unemployment, that is the probability of termination of the unemployment state, $h_j = \lambda_j \left[(1-p)(1 - G_j(\rho U_j) + p(1 - G_j(\rho U_j + dI_{[j=W]}) \right]$.[9]

Finally, the contribution to the likelihood of wages data assumes that observed wages are accepted and observed only for individuals participating in the labor market and 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 equations in (6); second, the resulting wage distribution is truncated to the range of accepted wages (that 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:

$$\begin{aligned} f_{ei}^o(w_s, w > \rho U_j, s \in U, s \in P|j) &= f_{ji}(w_s|w > \rho U_j, j) \Pr[s \in E|j] \Pr[s \in P|j] \\ &= \frac{\frac{p}{\beta} g_j \left(\frac{w_s + \beta dI_{[j=W,i=P]} - (1-\beta)\rho U_j}{\beta} \right)}{1 - G_j(\rho U_j + dI_{[j=W,i=P]})} \left[\frac{h_j}{\eta_j + h_j} R_j \left(\rho U_j \right) \right] Q_j(z_j^*) \end{aligned} \tag{14}$$

Because the type of employer is not observed, $f_{eN}^o(\cdot)$ contributes with probability $1-p$ and $f_{eP}^o(\cdot)$ 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 that the value of out-of-the-labor-market activities z and the entrepreneurial ability y follow a negative exponential distribution, that is $Q_j(z) = 1 - e^{-\gamma_j z}$

[9] 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 particular case of Argentina, where the structure of the duration data is defined as intervals, the contribution of the duration data uses $\left[1 - e^{-h_j t_s^{(2)}}\right] - \left[1 + e^{-h_j t_s^{(1)}}\right]$, for the interval of durations $t_s^{(2)} - t_s^{(1)}$, instead of the negative exponential density function.

and $R_j(y) = 1 - e^{-\theta_j y}$, respectively.[10] 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.

Putting equations (11) to (14) together, the log-likelihood function to be maximized, choosing the set of parameters Θ, is:

$$\ln L(w,t,U,E,S,NP;\Theta) = \tag{15}$$
$$\sum_{j=M,W}\left\{\sum_{s=1}^{N_{j,NP}}\ln\Pr[s\in NP|j] + \sum_{s=1}^{N_{j,S}}\ln\Pr[s\in S, s\in P|j] + \sum_{s=1}^{N_{j,U}}\ln f_t(t_s, s\in U, s\in P|j) + \right.$$
$$\left.\sum_{s=1}^{N_{j,E}}\ln\left((1-p)f^o_{eN}(w_s, w>\rho U_j, s\in U, s\in P|j) + pf^o_{eP}(w_s, w>\rho U_j, s\in U, s\in P|j)\right)\right\}$$

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.[11] 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[12]. 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 enough information for the estimation of parameter γ_j, again under the assumption of a negative exponential distribution for z.

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 (15) can be estimated choosing only the following parameters $\Theta' =$

[10] 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 (we can only fit a one-parameter distribution).

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

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

$\{\lambda_M, \lambda_W, \eta_M, \eta_W, \mu_M, \sigma_M, \mu_W, \sigma_W, p, d\}$. 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[13]. 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; that is, 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 on top of the parameters of the productivity distributions is that those distributions belong to a location-scale family.[14] Under this family of distributions, parameters p and d distorts the shape of the implied wage distribution of the model (a mixture of distributions by gender), particularly in the slope of the low tail of the distribution (Flabbi, 2010a). The log-normal satisfies this condition again.

Finally, as is usual in the literature that estimates structural search models with supply side data, we do not attempt to identify 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). Additionally, parameters ρ and b are not separately 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).

[13] In steady state, the flows in and out of unemployment should be equal in order to maintain the number of unemployed and employed workers constant.

[14] 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.

4 Estimation Results

Table 2 presents the estimated parameters. Rows one and two show the estimates of the Poisson rate at which workers meet potential employers. There is considerable heterogeneity among these Latin American countries in terms of how often job offers arrive, but no pattern can be found by gender. Job offers arrive after an average period ranging 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 much 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 conveys information on the average duration of a job, are shown in rows three and four. 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 for which jobs last longer, regardless of gender. In these countries, jobs last between 11 and 22 years and between 8 and 33 years for men and women, respectively. On the contrary, in Colombia, Mexico, and Peru, jobs last at most 3 years, on average. In two countries, Bolivia and Paraguay, job duration for women is very high relative to men's (60%-100% higher). In contrast, job duration for men almost double job duration 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 five to eight). Given the log-normality assumption, the average productivity implied in those estimates is shown by gender in the second row of the top and middle panels of Table 3.[15] In five of the nine countries, average productivity is higher for

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

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 nine and ten show the estimates of the intensity of discrimination and the proportion of prejudiced employers. Two comments are worth mentioning before presenting the results. First, according to the likelihood ratio test (LR), found in the last row of the table, the null hypothesis of no prejudiced employers in the economy ($p = 0$) and no disutility of hiring a woman ($d = 0$) is rejected for all countries, except Colombia.[16] Second, the intensity of discrimination is not directly comparable across countries and skill levels because workers have different productivity in both dimensions. In order 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 discrimination section of Table 2 shows the measure of relative intensity and the proportion of total workers whose employer is prejudiced. Two main facts emerge. First, the intensity of discrimination ranges between 12.5 and 41% of the average productivity of men. The lowest intensity of discrimination is found in 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 highest rate is observed in Paraguay (almost 43%).

Rows eleven and twelve show the estimates of the reservation wages by gender. In all countries, except for Argentina, Bolivia, Mexico, and Paraguay, men's reservation wage tends to be higher than that of women (from 5 to 22%), which implies that employers

[16] Given these results, we impose $p = d = 0$ only for Colombia in the counter-factual and policy experiments.

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 the last four rows of the table.

Regarding the goodness of fit of the model, Table 3 presents the model predictions for several measures. Comparing these predictions to the descriptive statistics in Table 1 shows that the overall fit of the model is very good for all countries.

5 Sources of Gender Gaps

5.1 Decomposition

In order to analyze the effect of each potential source on gender gaps, we perform a set of counter-factual experiments. In each experiment, one potential source of the gender wage gap was turned off, and the ratio of wages between women and men was calculated for the average and for the top and bottom 25% of the wages distribution. We also computed gaps in unemployment, employment, self-employment and participation. Since we compute the resulting equilibrium in the model for each counter-factual scenario, we are able to separate, while taking into account changes in agents decisions, the individual effect of gender differences in productivity, in the arrival rate of jobs and in the discrimination intensity. While we are able analyze the individual impact of these three sources of gender gaps, we cannot disentangle all the mechanisms behind each of them.[17] Regardless of this limitation, we discuss the relationship between some gender institutions in the Latin American countries and the intensity of discrimination estimated with the model in the next subsection.

In the first experiment (called Productivity) we analyze how important productivity differences are by equalizing the productivity distributions between women and men (we set

[17]Gender differences in termination rates, arrival rates or productivity could reflect differences in search strategies or ability of networking, among other things. We are not able to identify the mechanism behind each result. We only model the effect of prejudice on wages and employment decisions.

the point estimates of μ and σ for 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 at zero. Finally, in the third experiment (called Transitions) we analyze the role of gender differences in labor market dynamics. In this case, we set the arrival rates of jobs and involuntary separations at the point estimates for men.

The gap (women's outcome relative to men's) that each experiment generates[18] is presented Table 4. Additionally, for comparison purposes, the gap predicted by the model, with all parameters set at their point estimates, is presented as Total Gap. Column one presents the mean wage gap, while columns two and three present wage gaps at the bottom and top quartiles (25%) of the wage distribution. Columns four to seven present the predicted gaps in all states of the labor market. Figure 1 shows gaps in the data and under the different scenarios.

In the multiple scenarios considered in the counter-factual experiments, some patterns regarding wage, participation, self-employment, unemployment, and employment rate gaps arise (see Figure 1).

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: relative participation and employment rates would fall, while self-employment rates would increase. On average, wage ratios would drop, meaning 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-employment

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

rates. Average wage ratios would increase and, in all countries except for Chile, higher gains would be found at the top quartile 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 mostly 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 any case. Average wage ratios are higher (wage gaps are reduced) and, in four countries (Argentina, Bolivia, Mexico, and Uruguay), average wage ratios become favorable for women (see Table 4). In all countries, a stronger effect is found for low wage earners. Three countries stand out in terms of 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 quarter, gaps become favorable for women, who in turn earn 40% more than men. At the bottom, 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: when prejudice is turned off, wage gaps become favorable for women on average (wage ratios are 1.16 and 1.08, respectively) and for the first quartile (1.54 and 1.38, respectively). At the top, the wage gap between women and men vanishes in Mexico and grows from 0.86 to 0.93 in Uruguay. In Uruguay, wage gaps are small, but prejudice plays an important role in any case.

In five countries (Argentina, Bolivia, Colombia, Paraguay, and Peru), labor market dynamics are a very important source of gender wage differentials. Labor market dynamics hurt women in these countries; hence, if we neutralize them, relative participation and employment rates increase, while self-employment rates decrease. Wage ratios would also improve, on average and on the top, but mostly for low-wage earners. In fact, in these five countries, average wage ratios become favorable for women in this scenario. On the contrary, in

Chile and Mexico, labor market transitions favor women; that is, 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.

To sum up, 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 on average and 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 hurt women in the remaining six countries. Once again, larger effects are found at the bottom of the distribution.

5.2 Discussion on the Mechanisms

We have estimated a model in which the existence of prejudiced employers generates large gender gaps in wages and other labor market outcomes. As explained in 2.4, the existence of prejudiced employers have both a direct and an indirect effect. On one hand, prejudiced employers penalize women by offering them lower wages and increasing the match-specific threshold for hiring them. On the other hand, the presence of prejudiced employers lowers women's outside option, regardless of the employer type. Women are more likely, then, to remain out of the labor force or become self-employed.

One way to rationalize the presence of prejudiced employers and the existence of d, is to consider the existence of specific labor market policies (such as maternity leave, nursing breaks) that may increase the cost of hiring women. These policies may increase the direct monetary cost or they may disrupt or introduce uncertainty in working schedules, which in turn, increase production costs. A fraction p of employers exhibit higher aversion to this potential thread, and therefore offer smaller wages to women. We could hypothesize that the stronger the protection offered to women, the higher the gender gap in wage offers (d).

All Latin American countries, in line with ILO recommendations, are very generous concerning maternity policies (see Addati et al., 2014). We characterize and rank the countries in our sample by constructing a pro-women's legislation index (hereafter pro-women index) that characterizes the existence of such provisions and their generosity. A detailed description of the construction of our index can be found in the online appendix B.

In order to check the robustness of the ranking to different specifications, we define two versions of the index.[19] Table 5 shows that regardless of the definition of the index, there is a clear ranking. The countries with the highest pro-women index are Chile, Bolivia, and Mexico, while those with the lowest cost of hiring women are Colombia and Paraguay, followed by Peru and Uruguay. It is also relevant to take into account the coverage of pro-women's policies. Uruguay and Chile are the two countries with the highest coverage, while Paraguay is the one with the lowest. Chile is precisely one of the countries with the highest pro-women index and the highest coverage, while Paraguay is at the opposite end, wtih low protection and low coverage. There is not a clear pattern for the others. This is an important issue to notice, as low coverage might dampen the effect of a strong protection legislation.

Our pro-women index is aligned with the discrimination intensity measure estimated by the model. Chile and Mexico have the highest estimated discrimination intensity. We hypothesize that employers perceive that hiring women might be costly, and therefore adjust wage offers. In a sense, some employers might just be following a cost-controlling strategy.

[19]In the online appendix we provide a comprehensive review of maternity legislation for all the countries in our sample, as well as a detailed description on the construction of our cost index. All the data is taken from Addati et al. (2014).

At the other end we have countries, such as Ecuador, Peru and Paraguay, for which our model predicts the lowest discrimination intensity measure in the sample. Accordingly with our pro-women index, Ecuador has standard maternity policies in place but it is one of the countries for which ILO estimates one of the lowest effective coverage. This could explain the low discrimination intensity estimates. On the contrary, Paraguay and Peru systematically rank low in our pro-women index. These two countries rank low in our protection 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 countries (9-18 months). Colombia, the country for which our model rejects the existence of discrimination, is the country with the lowest relative protection index in our sample. It is also one of the countries (the other is Peru) that has enacted (by law) an equal pay policy that is subject to reporting requirements[20]. This fact alone could explain our results.

6 Policy experiments

We use the model to analyze the potential impact of two different labor market policies aimed at mitigating gender gaps: a hiring subsidy and an equal-pay policy. In the first case, a subsidy is offered to all employers. In the second, a law is passed, forcing all employers to pay equal wages to both women and men. In both cases, we measure the impact of the policy on worker's welfare and other labor market outcomes such as wages, unemployment duration, and labor market participation, among others.[21] Results are presented in Table 6. Panel A, labeled "Base Model", shows the base scenario, with no policy. The first three rows show welfare measures for both women and men and for the whole sample. The last six rows show gaps in reservation wages, unemployment, self-employment and participation rates, unemployment duration, and average wages.[22] As expected, women achieve a lower

[20] See Table B.1 in the online appendix B.

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

[22] All gaps are expressed as women/men ratios.

welfare level than men. Chile, Peru, Colombia, and Ecuador (in this order) display the largest welfare gaps between men and women.

Panel B, labeled "Affirmative Action Policy", shows the 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 recovered endogenously to balance the government budget). We observe that welfare falls for men (at most 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. In terms of labor market outcomes, the policy reverts the wage gap in favor of women in five countries. The largest effects are found in Mexico and Chile, where wage gaps change the most and even become favorable for women.[23] 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 plummet. Again, the maximum effect is found in Chile and Mexico, where discrimination intensity is highest.

Panel C, labeled "Equal Pay Policy", shows a scenario in which 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 base scenario.As this policy neutralizes wage gaps for men and women of equal productivity, differences in average wages are due to differences in average productivity in both groups. In this scenario, men's welfare drops more than in scenario B. The smallest impact is observed in Colombia (2 percentage points), while the greatest impact is 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; the largest reduction is found in Mexico (13 percentage

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

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 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 convergence in participation rates, but reduces relative self-employment rates and increases (relative) unemployment for women.

To sum up, both policies generate convergence in wages, but the largest reduction (which generates an equilibrium in which women's wages are higher than men's) is caused by the affirmative action policy. As a result of this policy, Chile and Mexico are the countries where women's wages improve the most, followed by Argentina, Bolivia, and Uruguay. As for the equal-pay policy, it shifts relative wages in women's favor in Argentina (6.7%), Mexico (5%), Bolivia and Ecuador (3%). All these effects are smaller than those originated by the affirmative action policy. Nevertheless, the equal pay policy scenario does generate more drastic changes in other measures, such as relative unemployment, participation and self-employment rates. These effects are particularly strong in two countries (Chile and Mexico) where discrimination intensity is highest.

7 Final Remarks

This paper estimates a search model of the labor market with participation decisions, occupational choice, search frictions, match-specific heterogeneity, and taste discrimination 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 gender wage gaps observed in the data, not only on average but also at the top and bottom of the wage distribution.

The existence of prejudiced employers in the model generates wage gaps between men and women (direct effect), as well as lowers women's outside option (spillover effect); and, regardless of the employer type, women are less likely to participate and more likely to be self-employed. Our estimations and simulations show that prejudice is an important source of gender gaps, but not necessarily the main force. Differences in labor dynamics and productivity differences are also important. However, prejudice plays a larger role in explaining gender wage gaps among low-wage earners. For high wage earners the main source of wage gaps are productivity differences.

The limitation of the approach is that while we are able to analyze the individual impact of the sources of gender gaps, we cannot disentangle all the mechanisms behind each of them. We rationalize, however, the presence of prejudiced employers by the existence of specific labor market policies that may increase the cost of hiring women. Some employers, with high aversion to cost uncertainty, discount women wages. We could hypothesize that the stronger the protection offered to women, the higher the gap in wage offers between women and men (d). We find a strong correlation in rank between our pro-women index and the discrimination intensity measure estimated by the model. our model estimates the highest intensity of discrimination (d) for Chile and Mexico, countries that also rank the highest in our protection index. Argentina, Bolivia, and Uruguay, follow, holding a similar rank in discrimination intensity and protection rank. Finally the countries with the lowest cost of hiring women (Colombia, Paraguay and Peru) are also those that rank low in discrimination intensity. One country that does not fit in this rule is Ecuador, where maternity protection standards are quite strict. Moreover, Ecuador is one of the only countries where employers partially cover maternity subsidies (25%), and, along with Paraguay, Peru and Colombia, offers protection from dismissal only during maternity leave.

The simulation a hiring subsidy and an equal-pay policy, shows that the most effective policy is to subsidize women's wages. In Chile and Mexico, where discrimination intensity is highest, both policies have the stronger effects. In these two countries, the equal pay policy also has stronger effects, closing gaps in unemployment and participation and reducing women's self-employment rates. With these types of policies one should keep in mind, not only the most effective policy, but also the policy that is easiest to implement. Again, it seems more feasible to implement a hiring subsidy administrable through the tax system, rather than putting in place an effective equal-pay policy.

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Table 1: Descriptive Statistics

	ARG	BOL	CHI	COL	ECU	MEX	PAR	PER	URU
					Men				
N	2376	1969	6628	2604	2260	11039	1587	3898	5245
$Pr(U)$	0.024	0.024	0.049	0.084	0.024	0.064	0.018	0.032	0.022
$Pr(E)$	0.793	0.777	0.823	0.589	0.798	0.747	0.827	0.762	0.753
$Pr(SE)$	0.183	0.199	0.128	0.327	0.178	0.189	0.155	0.206	0.225
$Pr(P)$	0.974	0.940	0.954	0.964	0.981	0.935	0.970	0.960	0.980
$E(w\|E)$	12.61	7.21	15.34	6.84	9.36	7.42	9.93	7.69	10.31
$SD(w\|E)$	6.64	5.08	13.02	4.79	6.12	4.89	6.38	5.94	7.71
$E(t\|U)$	-	5.36	2.95	4.75	4.00	3.07	5.63	1.01	7.36
$SD(t\|U)$	-	5.82	3.61	5.59	3.95	3.76	5.58	1.38	6.74
					Women				
N	4013	1867	8190	3895	3096	16675	2380	4354	8137
$Pr(U)$	0.034	0.027	0.057	0.139	0.038	0.058	0.021	0.053	0.028
$Pr(E)$	0.839	0.785	0.852	0.590	0.853	0.790	0.863	0.747	0.802
$Pr(SE)$	0.127	0.189	0.091	0.271	0.109	0.153	0.116	0.200	0.170
$Pr(P)$	0.882	0.821	0.837	0.856	0.869	0.671	0.903	0.838	0.909
$E(w\|E)$	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				
N	-	-	-	-	-	-	-	-	-
$Pr(U)$	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
$Pr(SE)$	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: Duration data in Argentina is defined qualitatively.

Table 2: Estimated Parameters

	ARG	BOL	CHL	COL	ECU	MEX	PAR	PER	URU
λ_M	0.1178	0.1878	0.3453	0.2277	0.2543	0.3281	0.1799	0.9997	0.1368
	(0.0001)	(0.0283)	(0.0288)	(0.0159)	(0.0007)	(0.0003)	(0.0004)	(0.0921)	(0.0128)
λ_W	0.0743	0.0863	0.4250	0.2128	0.2294	0.3705	0.1026	1.0585	0.1328
	(0.0000)	(0.0138)	(0.0088)	(0.0099)	(0.0031)	(0.0002)	(0.0004)	(0.0785)	(0.0093)
η_M	0.0037	0.0058	0.0205	0.0306	0.0077	0.0288	0.0040	0.0419	0.0041
	(0.0000)	(0.0013)	(0.0007)	(0.0031)	(0.0001)	(0.0000)	(0.0000)	(0.0055)	(0.0005)
η_W	0.0030	0.0029	0.0226	0.0495	0.0103	0.0254	0.0025	0.0758	0.0047
	(0.0000)	(0.0006)	(0.0001)	(0.0034)	(0.0002)	(0.0000)	(0.0000)	(0.0078)	(0.0005)
μ_M	2.8979	2.2860	2.9383	2.0130	2.5145	2.3178	2.5866	2.3097	2.6394
	(0.0081)	(0.0194)	(0.0769)	(0.0314)	(0.0070)	(0.0007)	(0.0007)	(0.0151)	(0.0119)
σ_M	0.5940	0.7038	0.8544	0.8867	0.6987	0.7225	0.6884	0.7558	0.7115
	(0.0069)	(0.0147)	(0.0412)	(0.0241)	(0.0530)	(0.0002)	(0.0124)	(0.0116)	(0.0090)
μ_W	3.0576	2.4325	2.7418	2.0139	2.4455	2.4544	2.5965	2.3528	2.7884
	(0.0021)	(0.0904)	(0.0258)	(0.0211)	(0.0507)	(0.0013)	(0.0029)	(0.0643)	(0.0359)
σ_W	0.4392	0.5382	0.7166	0.8081	0.5503	0.5808	0.5379	0.6397	0.5376
	(0.0020)	(0.0420)	(0.0941)	(0.0166)	(0.0234)	(0.0005)	(0.0038)	(0.0321)	(0.0166)
d	6.0798	3.6799	11.1146	0.0000	1.9995	5.2041	2.9149	1.9167	4.2610
	(0.0016)	(1.8056)	(0.3178)	(0.0000)	(0.0531)	(0.0035)	(0.0199)	(1.8911)	(0.8744)
p	0.4988	0.4992	0.4964	0.5356	0.4995	0.4976	0.4995	0.5000	0.4989
	(0.0859)	(0.3740)	(0.9518)	(0.0000)	(0.5071)	(0.0301)	(0.2945)	(0.6722)	(0.1809)
w^*_M	3.6461	1.7512	3.2054	2.1018	2.7406	1.7238	2.8119	1.8280	2.3525
w^*_W	3.5927	1.7740	2.9589	1.6996	2.5057	1.6736	2.7932	1.4224	2.1771
θ_M	0.4660	0.9224	0.6403	0.5319	0.6302	0.9658	0.6626	0.8636	0.6334
θ_W	0.5747	0.9405	0.8116	0.7681	0.8847	1.1238	0.7729	1.1332	0.8141
γ_M	0.8988	1.4311	0.9039	1.2266	1.3031	1.4235	1.1554	1.5602	1.4407
γ_W	0.5601	0.8716	0.5908	0.9449	0.7718	0.6138	0.7912	1.1390	1.0049
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 3: Model Predictions

	ARG	BOL	CHL	COL	ECU	MEX	PAR	PER	URU
					Men				
$E(y)$	1.1126	0.6988	1.1063	0.8152	0.7674	0.7025	0.8655	0.6409	0.6941
$E(x)$	21.635	12.600	27.203	11.091	15.777	13.181	16.836	13.400	18.039
$SD(x)$	14.073	10.087	28.207	12.126	12.516	10.912	13.109	11.761	14.644
$E(w)$	12.641	7.176	15.204	6.597	9.259	7.453	9.824	7.614	10.196
$E(w\|E)$	12.673	7.216	15.444	6.992	9.366	7.494	9.913	7.687	10.245
$E(t\|U)$	8.519	5.364	2.952	4.754	3.995	3.069	5.625	1.012	7.356
$Pr(U)$	0.025	0.024	0.050	0.085	0.024	0.066	0.019	0.032	0.023
$Pr(E)$	0.792	0.777	0.822	0.588	0.798	0.745	0.826	0.761	0.752
$Pr(SE)$	0.183	0.199	0.128	0.327	0.178	0.189	0.155	0.206	0.225
$Pr(P)$	0.973	0.940	0.954	0.964	0.981	0.935	0.970	0.960	0.980
					Women				
$E(y)$	1.785	1.147	1.693	1.058	1.296	1.629	1.264	0.878	0.995
$E(x)$	23.430	13.162	20.056	10.385	13.422	13.778	15.505	12.902	18.781
$SD(x)$	10.808	7.630	16.430	9.968	7.982	8.726	8.981	9.174	10.871
$E(w)$	11.995	6.550	8.749	6.042	7.465	6.431	8.421	6.683	9.416
$E(w\|E)$	12.138	6.757	11.032	6.198	7.584	6.910	8.588	6.783	9.566
$E(t\|U)$	13.710	12.109	3.042	4.860	4.463	2.969	10.033	0.963	7.692
$Pr(U)$	0.035	0.027	0.058	0.141	0.039	0.059	0.022	0.054	0.029
$Pr(E)$	0.838	0.784	0.851	0.588	0.852	0.788	0.863	0.746	0.801
$Pr(SE)$	0.127	0.189	0.091	0.271	0.109	0.152	0.115	0.200	0.170
$Pr(P)$	0.882	0.821	0.837	0.856	0.869	0.671	0.903	0.838	0.909
					Women / Men				
$E(y)$	1.605	1.642	1.530	1.298	1.688	2.319	1.460	1.370	1.434
$E(x)$	1.083	1.045	0.737	0.936	0.851	1.045	0.921	0.963	1.041
$SD(x)$	0.768	0.756	0.582	0.822	0.638	0.800	0.685	0.780	0.742
$E(w)$	0.949	0.913	0.575	0.916	0.806	0.863	0.857	0.878	0.924
$E(w\|E)$	0.958	0.936	0.714	0.887	0.810	0.922	0.866	0.882	0.934
$E(t\|U)$	1.609	2.258	1.031	1.022	1.117	0.967	1.784	0.951	1.046
$Pr(U)$	1.412	1.125	1.175	1.654	1.601	0.904	1.178	1.685	1.267
$Pr(E)$	1.058	1.009	1.035	1.000	1.068	1.058	1.044	0.980	1.066
$Pr(SE)$	0.694	0.948	0.705	0.829	0.613	0.806	0.744	0.967	0.754
$Pr(P)$	0.906	0.873	0.877	0.888	0.886	0.717	0.930	0.873	0.928

Table 4: Counter-factual Experiments

Country	Closing	Wages			Labor Market States			
	Differences in:	Average	P25	P75	$Pr(U)$	$Pr(E)$	$Pr(SE)$	$Pr(P)$
ARG	Total Gap	0.958	1.017	0.889	1.412	1.058	0.694	0.906
	Productivity	0.892	0.782	0.939	1.383	0.991	0.988	0.865
	Prejudice	1.109	1.358	0.969	1.482	1.130	0.370	0.958
	Transitions	1.098	1.346	0.963	1.265	1.193	0.128	1.001
BOL	Total Gap	0.936	1.015	0.865	1.125	1.009	0.948	0.873
	Productivity	0.933	0.850	0.968	1.151	0.974	1.084	0.854
	Prejudice	1.074	1.357	0.935	1.181	1.106	0.564	0.937
	Transitions	1.183	1.686	0.986	1.420	1.221	0.085	1.040
CHL	Total Gap	0.714	0.811	0.668	1.175	1.035	0.705	0.877
	Productivity	1.369	1.967	1.221	1.542	1.123	0.005	1.043
	Prejudice	0.902	1.393	0.747	1.110	1.141	0.054	1.020
	Transitions	0.614	0.494	0.620	0.746	0.623	3.512	0.625
COL	Total Gap	0.887	0.892	0.863	1.654	1.000	0.829	0.888
	Productivity	0.997	0.991	0.998	1.872	1.084	0.621	0.923
	Prejudice	0.887	0.892	0.863	1.654	1.000	0.829	0.888
	Transitions	1.037	1.280	0.940	1.394	1.322	0.319	0.981
ECU	Total Gap	0.810	0.919	0.739	1.601	1.068	0.613	0.886
	Productivity	1.058	1.154	1.031	1.860	1.153	0.196	0.967
	Prejudice	0.882	1.081	0.777	1.647	1.116	0.389	0.927
	Transitions	0.855	1.034	0.762	1.173	1.143	0.336	0.937
MEX	Total Gap	0.922	0.941	0.878	0.904	1.058	0.806	0.717
	Productivity	0.906	0.767	0.958	0.873	0.971	1.160	0.655
	Prejudice	1.156	1.542	0.994	0.968	1.226	0.120	0.936
	Transitions	0.818	0.640	0.829	0.552	0.525	3.024	0.493
PAR	Total Gap	0.866	0.977	0.792	1.178	1.044	0.744	0.930
	Productivity	0.997	1.013	0.999	1.290	1.086	0.509	0.960
	Prejudice	0.951	1.166	0.837	1.197	1.088	0.507	0.960
	Transitions	1.027	1.385	0.873	1.278	1.159	0.122	1.013
PER	Total Gap	0.882	0.906	0.844	1.685	0.980	0.967	0.873
	Productivity	0.971	0.936	0.987	1.910	1.070	0.599	0.929
	Prejudice	0.985	1.171	0.895	1.904	1.120	0.415	0.961
	Transitions	1.035	1.332	0.919	1.309	1.221	0.137	1.013
URU	Total Gap	0.934	1.021	0.857	1.267	1.066	0.754	0.928
	Productivity	0.913	0.792	0.957	1.236	0.996	0.989	0.899
	Prejudice	1.075	1.384	0.927	1.389	1.192	0.321	0.984
	Transitions	0.950	1.065	0.865	1.137	1.115	0.602	0.947

Table 5: Pro-Women Index vs Relative Discrimination

	Cost Index		Cost Index (excl. subs. paid by employers)		Effective coverage		Relative discrimination Measure	
	Index	Ranking	Index	Ranking	Index	Ranking	Index	Ranking
Argentina	0.35	5	0.43	5	0.36	6	0.28	4
Bolivia	0.73	2	0.66	2	0.36	5	0.29	3
Chile	0.80	1	1.00	1	1.00	1	0.41	1
Colombia	0.21	9	0.27	9	0.73	3	-	-
Ecuador	0.40	4	0.47	4	0.10	9	0.13	8
Mexico	0.42	3	0.50	3	0.36	8	0.39	2
Paraguay	0.26	8	0.32	8	0.36	7	0.17	6
Peru	0.29	7	0.36	7	0.73	4	0.14	7
Uruguay	0.31	6	0.39	6	1.00	2	0.24	5

Table 6: Policy Experiments

	ARG	BOL	CHL	COL	ECU	MEX	PAR	PER	URU
Panel A: Base Model									
Welfare Measures									
Men	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Women	0.936	0.900	0.591	0.759	0.786	0.880	0.865	0.695	0.906
Total	0.960	0.951	0.774	0.856	0.876	0.928	0.919	0.839	0.943
Labor Market Variables (Women/Men)									
Reservation Wage	0.985	1.013	0.923	0.809	0.914	0.971	0.993	0.778	0.925
Unemployment Rate	1.412	1.125	1.175	1.654	1.601	0.904	1.178	1.685	1.267
Self-Employment Rate	0.694	0.948	0.705	0.829	0.613	0.806	0.744	0.967	0.754
Participation Rate	0.906	0.873	0.877	0.888	0.886	0.717	0.930	0.873	0.928
Unemployment Duration	1.609	2.258	1.031	1.022	1.117	0.967	1.784	0.951	1.046
Average Wage	0.958	0.936	0.714	0.887	0.810	0.922	0.866	0.882	0.934
Panel B: Affirmative Action Policy (subsidy)									
Welfare Measures									
Men	0.992	0.988	0.956	1.000	0.996	0.953	0.996	0.983	0.986
Women	0.979	0.944	0.655	0.759	0.805	0.947	0.890	0.723	0.951
Total	0.984	0.966	0.790	0.856	0.886	0.950	0.933	0.846	0.964
Labor Market Variables (Women/Men)									
Reservation Wage	1.060	1.100	1.171	0.809	0.952	1.195	1.038	0.856	1.017
Unemployment Rate	1.446	1.156	1.245	1.654	1.620	0.974	1.191	1.750	1.314
Self-Employment Rate	0.609	0.830	0.419	0.829	0.566	0.565	0.683	0.831	0.649
Participation Rate	0.914	0.887	0.921	0.888	0.891	0.756	0.935	0.887	0.937
Unemployment Duration	1.606	2.246	1.021	1.022	1.115	0.963	1.778	0.950	1.043
Average Wage	1.184	1.179	1.081	0.887	0.914	1.265	1.007	1.008	1.133
Panel C: Equal Pay Policy									
Welfare Measures									
Men	0.877	0.880	0.722	0.974	0.939	0.756	0.928	0.889	0.869
Women	0.997	0.985	0.701	0.774	0.825	1.010	0.902	0.778	0.986
Total	0.953	0.931	0.710	0.854	0.873	0.908	0.912	0.830	0.940
Labor Market Variables (Women/Men)									
Reservation Wage	1.287	1.361	1.931	0.870	1.078	1.874	1.164	1.132	1.310
Unemployment Rate	1.523	1.215	1.357	1.705	1.667	1.112	1.213	1.941	1.431
Self-Employment Rate	0.438	0.596	0.169	0.760	0.448	0.285	0.550	0.533	0.442
Participation Rate	0.936	0.922	1.010	0.896	0.906	0.838	0.949	0.930	0.961
Unemployment Duration	1.566	2.156	0.918	1.013	1.099	0.898	1.741	0.939	1.017
Average Wage	1.067	1.033	0.803	0.908	0.861	1.052	0.923	0.961	1.028

Note: All welfare measures are relative to those of men in the base model.

Figure 1: Gender Gaps in Labor Market Outcomes under Different Counter-factual Scenarios