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 taste discrimination for skilled workers in nine Latin American countries. The impact of pure discrimination from the influence of other gender-specific labor market characteristics is identified. Prejudice is the only source of wage gaps that consistently hurts women, however it is not the main driving force. Productivity differences are an equalizing source, while labor market dynamics generate large wage differentials. We also analyze the effects of two policies: a hiring subsidy and an equal-pay policy. The former is the most effective in reducing wage gaps.

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1 Introduction

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 (henceforth GGGR), 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.

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Labor economics literature on wage gaps is vast and is mostly based on the human capital theory. Several methodological approaches have been used to evaluate gender wage gaps[1]. One of the most popular procedures is the classic decomposition of Oaxaca (1973) and Blinder (1973), subsequently generalized by Oaxaca and Ransom (1994) and Neumark (1988). In this technique, wage differentials between men and women are decomposed[2] into the portion explained by differences in human capital endowments (and other observables) and their returns. The portion of the predicted means not related to endowments is interpreted as discrimination[3]. Despite its popularity, this approach has several limitations.

First, focusing only on differences in the returns of observables might be a biased estimate of discrimination because unobservables such as motivation, ability, or preferences are part of this residual[4]. Juhn et al. (1993) extended the methodology to include a third component –unobserved heterogeneity. Second, the Oaxaca-Blinder decomposition is only informative regarding the average wage gap. Several authors have proposed alternative methodologies that rely on non-parametric estimations (DiNardo et al., 1996) and resort to estimating a parametric model for the quantiles of the conditional distribution, after which they propose a variety of methodologies to recover the counter-factual distributions (Machado and Mata, 2005; Melly, 2005). Third, the distribution of men and women differs across jobs and sectors (segregation), which could be explained by discrimination, preferences, or job availability at a given point in time (that is, labor market frictions). Adding dummy variables for sectors or occupations in the wage regression to account for such differences, which is equivalent to assuming that there is no preemptive discrimination in accessing occupations and sectors, could lead to interpreting (causally) that a larger fraction of the wage gap is related to these "observables". Moreover, as pointed out in Ñopo (2008), when sector or occupational dummy variables are included in the parametric wage model, it is assumed that the linear estimated coefficients are valid outside of the common support of observables (for both women and men). Ñopo (2008) proposes the use of matching techniques to overcome the criticism that this approach only focuses on gaps in mean wages and solve the problem of women and men having different support over observables.

In any case, all these approaches cannot be used to evaluate policies against discrimination because they do not take into account the effect of the policy on agents' (workers and employers) behavior. In other words, all these approaches can be useful for describing wage

[1]A good literature review on this topic can be found in Gunderson (2006), Altonji and Blank (1999), Blau (1998) and Blau and Kahn (2000), among others.

[2]In this literature, methods generally used are the Oaxaca and Blinder decomposition (parametric or non-parametric) or the Mincer wage equations.

[3]This procedure was extended by Juhn et al. (1993) by taking into account the residual distribution.

[4]Atal et al. (2010) estimate that the unexplained part of the wage gap is quite sizable for Latin American countries.

gaps but they cannot solve the fundamental identification problem, that is, how to separate the impact of pure discrimination from other gender-specific labor market 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 (or at least, part of them)[5]. More recent literature on gender gaps and their determinants uses a structural approach. In this case, a (stylized) theoretical model of the dynamics of the labor market is estimated using micro-data to evaluate and quantify the role of productivity, preferences, and discrimination on gender gaps.[6] In this approach, the decision-making process of workers and employers and all the unobservables are explicitly modeled, after which the particular structure of the model is exploited to identify these components from the data. The strengths of this approach are twofold: first, the assessment of policies is less vulnerable to the Lucas critique and second, it allows for the construction of counter-factual scenarios (which are useful analyze the sources of the gap).

In this paper, we use this structural approach to study gender gaps in nine Latin American countries: Argentina, Bolivia, Chile, Colombia, Ecuador, Mexico, Paraguay, Peru, and Uruguay. In particular, we estimate a search model of the labor market where participation decisions, occupational choice, search frictions, match-specific heterogeneity, and taste discrimination (à la Becker) are allowed. This type of model is standard in the current state of the literature (Flabbi, 2010b). Even though the model is highly stylized, making it manageable, it is rich enough in its dynamics to take into account the various potential sources of gender gaps.

The labor market environment is simple and can be summarized as follows: the economy is populated by four types of agents –male and female workers, and prejudiced and unprejudiced employers. Prejudiced employers assign a lower value to a given labor relation when they hire a woman. The first decision is made by the workers. They decide whether to participate or not in the labor market according to how much they value activities different from those of the labor market. If the worker participates, he/she decides whether to search for a wage job and become unemployed or to start a venture (that is, become self-employed). Only unemployed agents search for a wage job. Employers also search for workers trying to fill their vacancies. Once a worker and an employer meet, they realize the value of the labor relationship and the employer's type (this information is not available ex-ante). Also, they negotiate the wage and the labor contract is signed only if it is worth it for both parties. If it is not, they continue their search for the next potential match. If the labor relation is

[5]See Flabbi (2010a) for a detailed explanation.

[6]See Flabbi (2010a) for a detailed literature review on this approach.

formed, the worker starts to work and receives the agreed wage. Of course, the relationship can be terminated at any time and both agents start their search again. On-the-job search is not allowed.

We followed the identification strategy developed by Flabbi (2010a) to estimate the proportion of prejudiced employers and the average intensity of discrimination against women, while at the same time allowing for gender-specific productivity levels and gender-specific mobility degrees. We estimated the model only for skilled workers (workers with either a technical or university degree) and for workers who are wage earners.[7] Using the estimated model parameters, we built counter-factual scenarios to identify the relative impact of productivity differences, search frictions, and prejudice on gender wage gaps. Of course, this decomposition was performed by taking into account all the equilibrium effects (changes in the labor market environment induce individual agents to adjust their behavior). Finally, we analyzed the effect of two well-known policy experiments: a subsidy for hiring women and an equal pay policy.

The data requirements to apply this structural approach are not particularly stringent. Specifically, we used a cross-section database for each country with the following information: wages, hours worked, unemployment duration, gender, education level, and labor market status. These data can typically be obtained from the Household Surveys of many Latin American Countries.

The remainder of this paper is organized as follows. Section 2 describes the structural approach. Section 3 describes the data and provides background information on the countries analyzed. Section 4 presents and discusses the results of the estimation, while Section 5 presents our final remarks.

2 The Structural Approach

For the structural analysis, we followed the strategy developed by Flabbi (2010a) to identify explicit gender discrimination in the labor market in nine Latin American countries. This section presents the theoretical model used to decompose gender wage gaps into their sources and describes the structural estimation procedure followed. The methodological discussion in this paper is rather brief and informal. Our theoretical model extends the search and matching model of Flabbi (2010b) incorporating two important features of the labor markets in Latin American countries: non participation decisions and occupational choices. In this

[7] We do not distinguish between formal and informal workers among wage earners. Informality is a well known feature of Latin American labor markets and it is basically concentrated in low skilled workers (on average, around 40% of these workers are informal). Hence, this paper focuses on high skilled workers, for whom formality rates are around 90% on average.

setting, gender discrimination is defined as explicit prejudice against women and modeled as taste (disutility) discrimination à la Becker (1971). We structurally estimated the model through maximum likelihood methods using data on participation, wages, and unemployment duration. Identification conditions follow the results in Flinn and Heckman (1982) for standard search models and those in Flabbi (2010a) for the specific parametrization of the discrimination component of the model. Our counter-factual analysis tried to quantify the individual effect of discrimination and other (possibly unobserved) labor market gender characteristics on the observed gender wage and labor market states gaps. Finally, we analyzed two policy experiments, an equal pay policy and a subsidy for hiring women (affirmative action-type policy).

2.1 The Model

We assumed that time is continuous and that 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— which are 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 a draw from the gender-specific distribution $Q_j(z)$, from devoting their time to activities other than those of the labor market. Because 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. Also, differences in the distribution of z by gender capture the idea of differences between men's and women's likelihood of participating. Defining the value of non participation in the labor market for agent type j as NP_j, its flow value can be written as:

$$\rho NP_j(z) = z \quad j = M, W \tag{1}$$

An individual participating in the labor market has an innate productivity 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.[8] Innate productivity is only known once the individual decides to enter the market. While searching for a job, unemployed individuals receive a flow utility (or possibly disutility) b_j and meet a potential employer at Poisson rate λ_j. Once the meeting occurs, a match-specific productivity x is realized, which is a draw of the gender specific productivity

[8]Because of data restrictions that limit the identification strategy (in particular data on transitions across labor market states), we assume that there are no dynamics between the non participation and participation states and between the self-employment and unemployment states. This means that both decisions, to participate and to become self-employed, are made once and forever. Even though this probably limits the analysis of the dynamics of the labor market, it does not eliminate the possibility of having equilibrium interactions among states in the labor market.

distribution $G_j(x)$. Agents can meet one of the two types of employers who exist in the economy: prejudiced or unprejudiced. Employers are 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 in the economy. For an unprejudiced employer, on the other hand, hiring a man or a woman makes no difference. There is a proportion $1 - p$ of this type of employers.[9] Therefore, discrimination in the model takes the form of a taste-based explicit prejudice against women in line with Becker's (1971) ideas. After meeting and the realization of the match specific productivity, employers and employees engage in wage bargaining and decide whether to form the match or not. The decision is made based on a reservation productivity rule; any match with a productivity greater than or equal to x^*_{jP} if the employer is prejudiced and x^*_{jN} if the employer is unprejudiced is acceptable for the employer and the employee. Let U_j, $V_{jP}(x)$, and $V_{jN}(x)$ be the unemployment value, the value of being employed by a prejudiced employer in a match with productivity x, and the value of being employed by a unprejudiced employer in a match with productivity x, respectively. The flow value of being unemployed for a type j agent is:

$$\rho U_j = b_j + \lambda_j \left\{ p \int_{x^*_{jP}} \left(V_{jP}(x) - U_j\right) dG_j(x) + (1-p) \int_{x^*_{jN}} \left(V_{jN}(x) - U_j\right) dG_j(x) \right\} \quad j = M, W \tag{2}$$

If an individual decides to start a venture and become self-employed, he/she receives his/her productivity as flow income y and stays in that state forever. Defining the value of self-employment for agent type j as $S_j(y)$, the flow value of the self-employment state can be written as:

$$\rho S_j(y) = y, \qquad j = M, W \tag{3}$$

When a type j worker is employed by a type i employer, prejudiced (P) or unprejudiced (N), in a match with productivity x, he/she receives a flow income equal to the wage rate $w_{ji}(x)$. During the term of the match, involuntary separation shocks that lead to termination of the match arrive at gender specific Poisson rate η_j. In case of termination, the worker starts to look for a new job as unemployed and the dynamics of the model are reset. The flow value of being employed by a type i employer for a type j worker in a match with productivity x is, therefore:

$$\rho V_{ji}(x) = w_{ji}(x) + \eta_j \left(U_j - V_{ji}(x)\right) \quad j = M, W; i = P, N \tag{4}$$

On the other side of the market, the flow income received by an employer depends not only on

[9] The proportion of prejudiced employers is assumed to be exogenous.

productivity but also on his/her own type and on the type of the employee who is matched. In particular, 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 (explicit taste discrimination) and is a measure of discrimination intensity. Note that the larger the parameter d the higher the match specific productivity x should be for the job to be effectively created. If the employer is unprejudiced ($i = N$), he/she receives a flow income equal to productivity x regardless of the type of worker who is filling the job. In turn, for a type i employer, the flow cost of having a filled vacancy with a type j worker with productivity x is the wage rate $w_{ij}(x)$. Again, if an involuntary separation shock arrives, the match is terminated and the employer loses the value of the match and starts to search for a new worker to fill the vacant job. If $J_{ij}(x)$ is the value of a filled job for a type i employer matched with a type j worker with productivity x, then the flow value of a filled job is:

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

where $I_{[j=W,i=P]}$ is an indicator variable which is equal to 1 if $j = W$ and $i = P$ and zero otherwise. Equations (1) to (5) complete the description of the value functions that characterize the dynamics of the model. To close the model description, as is standard in the literature, we use the generalized axiomatic Nash bilateral bargaining outcome to determine wages. In particular, the wage rate solves the following problem:

$$\begin{aligned} w_{ji}(x) &= \underset{w_{ji}}{argmax} \left[V_{ij}(x) - U_j\right]^{\beta} \left[J_{ij}(x)\right]^{1-\beta} && (6) \\ &= \underset{w_{ji}}{argmax} \left[\frac{w_{ji} - \rho U_j}{\rho + \eta_j}\right]^{\beta} \left[\frac{x - dI_{[j=W,i=P]} - w_{ji}}{\rho + \eta_j}\right]^{1-\beta} && j = M, W; i = P, N \end{aligned}$$

where β is interpreted as the bargaining power of the worker. The solution to the optimization problem in (6) 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:

$$w_{ji}(x) = \beta \left(x - dI_{[j=W,i=P]}\right) + (1 - \beta)\rho U_j \quad j = M, W; i = P, N \tag{7}$$

The interpretation of the wage equation (7) is standard: workers are paid a weighted average, according to their bargaining power, of the match productivity, discounting the disutility of hiring a woman for a prejudiced employer, and their outside option (that is, the unemployment flow value). Note that the presence of parameter d in the wage equation (7) shows the direct effect of taste discrimination on wages.

The equilibrium of the model consists of a set of reservation values related to the decisions of participating given the realized utility z, choosing an occupation (searching decision) given the innate productivity y, and accepting a job given the realized productivity x. In a non participation decision, the individual solves the problem

$$\max\left\{NP_j(z), \int \max\left\{U_j, S_j(y)\right\} R(y)dy\right\}$$

and therefore the reservation value z_j^*, which makes the agent indifferent between participating or not in the labor market, satisfies $NP_j(z_j^*) = \int \max\left\{U_j, S_j(y)\right\} R(y)dy$. Replacing equation (1) in the last condition leads to $z_j^* = \int \max\left\{\rho U_j, \rho S_j(y)\right\} R(y)dy$, which means that any agent with a value z greater than the expected value of entering the labor market will not participate in it. In the case of occupational choice, the individual solves the following problem:

$$\max\left\{U_j, S_j(y)\right\}$$

and therefore the reservation value y_j^* satisfies $\rho U_j = \rho S_j(y^*)$ or, using equation (3), $y_j^* = \rho U_j$. The decision is then to search for a wage job (as unemployed) if $y \leq y^*$ and start a venture as self-employed otherwise. Using the latter result, the threshold value of a non-participation decision becomes $z_j^* = \rho U_j R(\rho U_j) + \int_{\rho U_j} y r_j(y)dy$. Finally, in the case of the job accepting decision, type j individuals solve the following problem conditional on being an unemployed individual (with $y < y_j^*$) meeting a type i employer:

$$\max\left\{V_{ij}(x), U_j\right\}$$

In this case, the reservation productivity x_{ji}^* for $j = M, W$ and $i = P, N$ makes agent j indifferent between accepting a job with employer i or not, and therefore satisfies $U_j = V_{ji}(x_{ji}^*)$. Using equations (4) and (7), 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 $w_{WP}^* = w_{WN}^* = \rho U_W$. Note that the second effect of taste discrimination is a penalty on the requirements of hiring a woman (that is, prejudiced employers are pickier than unprejudiced employers when hiring a woman). Finally, as shown in Flabbi (2010a) (Proposition 1), 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 even when dealing with an unprejudiced employer. Additionally, in equilibrium, the presence of prejudiced employers makes women less likely to participate, with participating women being more likely to become self-employed.

Note that the equilibrium of the model, that is, the reservation values in all states of the labor market, can be completely characterized by the flow value of unemployment, ρU_j for $j = M, W$. Combining equations (2), (4), and (7), we have the Bellman equations that solve for ρU_M and ρU_W:

$$\begin{aligned} \rho U_j &= b_j + \frac{\lambda_j \beta}{\rho + \eta_j} \left\{ p \int_{\rho U_j + dI_{[j=W]}} \left(x - dI_{[j=W]} - \rho U_j \right) dG_j(x) \right. \\ &\left. + (1-p) \int_{\rho U_j} (x - \rho U_j)\, d_j G(x) \right\} \quad j = M, W \end{aligned} \tag{8}$$

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

$$u_j + s_j + e_j + np_j = 1$$

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. Conditioning on participation, the last equation can be rewritten as:

$$\tilde{u}_j + \tilde{s}_j + \tilde{e}_j = 1 \tag{9}$$

where the rate $\tilde{x} = x/(1 - np_j)$. Equation (9) holds for workers regardless of type according to their innate productivity y, that is $\tilde{u}_j(y) + \tilde{s}_j(y) + \tilde{e}_j(y) = 1$. According to the decision rules described above, $\tilde{s}_j(y) = 0$ for all $y < y^*$ and $\tilde{u}_j(y) = 0$ and $\tilde{e}_j(y) = 0$ for all $y \geq y^*$. Therefore, in steady state and for $y < y^*$, the flows in and out of unemployment from and to employment must be equal: $h_j \tilde{u}_j(y) = \eta_j (1 - \tilde{e}_j(y))$, where $h_j = \lambda_j \left[p\widetilde{G_j} \left(\rho U_j + dI_W \right) + (1-p)\, \widetilde{G}_j \left(\rho U_j \right) \right]$ is the hazard rate out of unemployment. The unemployment rate for type y workers is therefore $u_j(y) = \frac{\eta_j}{h_j + \eta_j}$. Aggregating the unemployment rate over y we have:

$$\tilde{u}_j = \int_0^{y^*} \tilde{u}_j(y) dR_j(y) = \frac{\eta_j}{h_j + \eta_j} R(y_j^*) \tag{10}$$

The employment rate, in turn, is $\tilde{e}_j(y) = \frac{h_j}{h_j+\eta_j}$ and aggregating over y yields:

$$\tilde{e}_j \quad = \quad \int_0^{y^*} \tilde{e}_j(y) dR_j(y) = \frac{h_j}{h_j + \eta_j} R(y_j^*) \tag{11}$$

The self-employed pool is formed only by workers with innate productivity $y \geq y^*$ and therefore the self-employed rate is:

$$\tilde{s}_j = 1 - R(y_j^*) \tag{12}$$

Finally, given that only individuals with a non-market value z lower than the reservation value z_j^* participate in the market, the participation rate in this economy can be computed as:

$$1 - np_j = 1 - Q_j(z_j^*) \tag{13}$$

We conclude this section presenting a welfare measure for this economy, which will be useful later on to evaluate the impact of the policy experiments. To accomplish this, we exploit the steady-state equilibrium of the model as in Flinn (2002). In particular, the welfare function of a worker type j with a value of non-market activities z, with innate productivity y, and working with a match-specific productivity x is:

$$W_j(x, y, z) = \left\{ \left[U_j \left(1 - I_{x \geq x_j^*} \right) + E_j(x) I_{x \geq x_j^*} \right] \left(1 - I_{y \geq y_j^*} \right) + S_J(y) I_{y \geq y_j^*} \right\} \left(1 - I_{z \geq z_j^*} \right) + NP_j(z) I_{z \geq z_j^*}$$

where $I_{x \geq x_j^*}$, $I_{y \geq y_j^*}$ and $I_{z \geq z_j^*}$ are indicator variables that take the value of 1 when its conditions is satisfied. To aggregate the welfare function, we use the equilibrium (ex-post) distributions of types in the population to weight individual measures, that is:

$$E[W_j(x, y, z)] = U_j \frac{\eta_j}{\eta_j + h_j} R_j(y_j^*) Q_j(z_j^*) + \int_{x^*}^{\infty} E_j(x) \frac{h_j}{\eta_j + h_j} R_j(y_j^*) Q_j(z_j^*) \frac{g_j(x)}{1 - G_j(x_j^*)} dx \tag{14}$$
$$+ \int_{y^*}^{\infty} S_j(y) \left[1 - R_j(y_j^*) \right] Q_j(z_j^*) \frac{r_j(y)}{1 - R_j(y_j^*)} dy + \int_{z^*}^{\infty} NP_j(z) \left[1 - Q_j(z_j^*) \right] \frac{q_j(z)}{1 - Q_j(z_j^*)} dz$$

where $S_j(y) = \frac{y}{\rho}$, $NP_j(z) = \frac{z}{\rho}$, and $E_j(x) = \frac{\beta(x - dI_{W,P}) + (1-\beta)\rho U_j + \eta_j U_j}{\rho + \eta_j}$. For $j = M$, the aggregated welfare function can be calculated directly using equation (14). For $j = W$, in turn, the welfare measure will be a linear combination of the aggregated welfare of women working with prejudiced and unprejudiced employers, each of them calculated using equation (14) and the appropriate definition of $E_j(x)$. This can be done because the proportion of prejudiced and unprejudiced employers is fixed (Flabbi, 2010a).

2.2 Estimation and Identification

The model described in the previous section 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 of Latin American countries. In particular, the data used includes labor market status of individuals, unemployment (outgoing) durations t_i observed for unemployed agents and hourly wages w_i observed for employer workers, by gender[10]. The model is estimated for skilled workers, who are defined as those who have completed tertiary education.

The likelihood function to be maximized, choosing the set of parameters Θ, is:

$$L(w,t,U,E,S,NP;\Theta) = \tag{15}$$
$$\prod_{j=M,W}\left\{\prod_{s=1}^{N_{j,NP}}\left[1-Q_j(z_j^*)\right]\times\prod_{s=1}^{N_{j,S}}\left[1-R_j\left(\rho U_j\right)\right]Q_j(z_j^*)\times\prod_{s=1}^{N_{j,U}}\left[h_j e^{-h_j t_s}\frac{\eta_j}{h_j+\eta_j}R_j\left(\rho U_j\right)Q_j(z_j^*)\right]\times\right.$$
$$\left.\prod_{s=1}^{N_{j,E}}\left[\left(\frac{\frac{(1-p)}{\beta}g_j\left(\frac{w_s-(1-\beta)\rho U_j}{\beta}\right)}{1-G_j(\rho U_j)}+\frac{\frac{p}{\beta}g_j\left(\frac{w_s+\beta d I_{[j=W]}-(1-\beta)\rho U_j}{\beta}\right)}{1-G_j(\rho U_j+dI_{[j=W]})}\right)\frac{h_j}{\eta_j+h_j}R_j\left(\rho U_j\right)Q_j(z_j^*)\right]\right\}$$

where

$$h_j = \lambda_j\left[(1-p)(1-G_j(\rho U_j)+p(1-G_j(\rho U_j+dI_{[j=W]})\right] \tag{16}$$
$$z_j^* = \rho U_j R(\rho U_j)+\int_{\rho U_j} y r_j(y)dy \tag{17}$$

The first component, the contribution to the likelihood of non-participation information, is the probability of not participating in the labor market which, conditional on the model, is $\Pr[z > z^*] = 1 - Q_j(z_j^*)$. The second component, the contribution to the likelihood of self-employment information, is the probability of being a self-employed worker $\Pr[s \in S] = 1 - R_j\left(\rho U_j\right)$, conditional on participating in the labor market, which happens with probability $\Pr[s \in NP] = Q_j(z_j^*)$. The third component, the contribution to the likelihood of duration data, is the probability density function of unemployment durations, $h_j e^{-h_j t_s}$, with h_j being the hazard rate out of unemployment[11], considering that those durations

[10] A description of the data is provided in section 3.

[11] Note that in the specification of the likelihood, unemployment durations have a negative exponential distribution, which is a direct consequence of a constant hazard rate conditional on the model (that is, it

are observed only for individuals who are participating and unemployed (the probabilities of participating and being unemployed, conditional on the model, are $\Pr[s \in NP] = Q_j(z_j^*)$ and $\Pr[s \in U] = \frac{\eta_j}{h_j+\eta_j} R_j(\rho U_j)$, respectively). The hazard rate out of unemployment, presented in equation (16), is the probability of termination of the unemployment state, which can occur if the match specific productivity with any type of employer is high enough (greater than the employer-specific reservation productivity).[12] The last component, the contribution to the likelihood of wages data, is a mixture by type of employer of the observed wage distributions implied by the model, considering that those wages are observed only for individuals who are participating and employed (the probability of being employed, conditional on the model, is $\Pr[s \in E] = \frac{h_j}{\eta_j+h_j} R_j(\rho U_j)$). The construction of the density of observed wages involves two steps: first, the productivity distribution $g_j(x)$ is mapped into the wage distribution through the wage equations in (7); second, the resulting wage distribution is truncated to the range of accepted wages (that is, all wages greater than the reservation wage). The resulting densities of accepted wages are:

$$f_{jN}^o(w) = \frac{\frac{1}{\alpha} g_j\left(\frac{w-(1-\alpha)\rho U_j}{\alpha}\right)}{1 - G_j(\rho U_j)}$$

and

$$f_{jP}^o(w) = \frac{\frac{p}{\alpha} g_j\left(\frac{w+\alpha d I_{[j=W]}-(1-\alpha)\rho U_j}{\alpha}\right)}{1 - G_j(\rho U_j + d I_{[j=W]})}$$

for unprejudiced and prejudiced employers, respectively. Finally, 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 follows a negative exponential distribution, that is, $Q_j(z) = 1 - e^{-\gamma_j z}$. Second, because information on self-employment earnings is typically very noisy in Latin American countries, we do not attempt to fit the distribution of those earnings; instead, we only use 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). Therefore, we assume that the innate productivity y follows a negative exponential distribution, that is, $R_j(y) = 1 - e^{-\theta_j y}$. 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. Both distributions are invertible. Using all these parametric assumptions, the likelihood function in equation (15) is maximized choosing the following set of parameters:

does not show duration dependence).

[12] In the case of Argentina, where the structure of the duration data is defined as intervals, the contribution to the likelihood of the duration data is $\left[1 - e^{-h_j t_s^{(2)}}\right] - \left[1 + e^{-h_j t_s^{(1)}}\right]$ for the interval of durations $t_s^{(2)} - t_s^{(1)}$.

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

Following Flinn and Heckman (1982), the reservation wage can be estimated using the minimum observed wage in the sample of employed workers[13], that is:

$$\hat{w}_j^* = \rho \hat{U}_j = \min \left\{ w_i^{obs} \right\}_{i=1}^{N_{j,E}}$$

As in Flabbi (2010a), we drop 5% of the lowest observations when estimating the reservation wage. Additionally, the likelihood estimation of parameter θ_j, under the assumption of a negative exponential distribution for y, is:

$$\hat{\theta}_j = \frac{\log\left(\frac{N_{jU}+N_{jS}+N_{jE}}{N_{j,S}}\right)}{\rho \hat{U}_j}$$

Note that this estimator only makes use of the estimated reservation wages and the proportion of the population that does not participate in the labor market by gender. Similarly, the likelihood estimation of parameter γ_j, under the assumption of a negative exponential distribution for y and given the estimated values of $\rho \hat{U}_j$ and $\hat{\theta}_j$, is:

$$\hat{\gamma_j} = \frac{\log\left(\frac{N_{jU}+N_{jS}+N_{jE}+N_{j,NP}}{N_{j,NP}}\right)}{\rho \hat{U}_j R(\rho \hat{U}_j) + \int_{\rho \hat{U}_j} y r_j(y) dy}$$

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:

$$\Theta' = \{\lambda_M, \lambda_W, \eta_M, \eta_W, \mu_M, \sigma_M, \mu_W, \sigma_W, p, d\}$$

As discussed in detail in Flabbi (2010a), the rate at which workers and potential employers meet (λ_j) is identified from the unemployment duration data (or the hazard rate out of unemployment), while both λ_j and the steady state condition are necessary to identify the arrival rate of involuntary shocks[14]. In turn, productivity distributions are identified from the observed wage distributions using the mapping from productivity to wages and the truncation point at the reservation productivity. The condition that makes this identification possible is the invertibility feature of the log-normal distribution, that is, the original distribution can

[13]In fact, Flinn and Heckman (1982) show that the minimum observed wage is a strongly consistent estimator of the reservation wage.

[14]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.

be recovered from a truncated distribution (Flinn and Heckman, 1982). 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. 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[15], we do not attempt to identify parameter α —the bargaining power of workers in the Nash bargaining game[16]— and instead set its value at 0.5.

We estimate two different models. In the first model, there is complete heterogeneity by gender in the parameters in both the labor market dynamics and the productivity distributions, but there is no prejudice ($d = p = 0$). The second model, in turn, has complete heterogeneity in all parameters and allows prejudice. Afterward, the best estimated model (using a log-likelihood ratio test) is used to perform the counter-factual and policy experiments. Due to space considerations, the estimation results discussed in the next section only show the estimates of the best model, but all results are available upon request.

3 Background and Data

3.1 Gender Disparities in Latin America

Most Latin American countries have grown considerably in the last 10 years (or so), 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. Indeed, income inequality has been historically high and persistent in these countries (particularly in Brazil, Colombia, Mexico, and Chile), making the region one of the most unequal worldwide (OECD, 2016). In addition, gender wage gaps are quite large in Latin America, with ethnic wage differences being even greater (Atal et.al., 2009).

The current state of gender disparities in Latin American countries is well depicted in the *Global Gender Gap Report 2014,* published by the World Economic Forum (henceforth GGGR). This report presents gender gap indices for 142 countries. These indices quantify the magnitude of the disparities between men and women across four areas (health, education,

[15] See Eckstein and van den Berg (2007) for a complete survey.

[16] Additionally, parameters ρ and b are not separately identified because both affect the reservation values. To identify b, ρ is set and the equilibrium condition and the estimates for the reservation wages are used. The values of ρ for each country are borrowed from Lopez (2008).

economy, and politics) and track their progress over time (Word Economic Forum, 2014). According to this report, major progress has been made in closing educational, health, and political empowerment gender gaps in most countries. However, sizable gender gaps still persist in the labor market. As a consequence, the region fell to the fourth place on the GGGR 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 as comparison measures.

Figures 1 to 4 illustrate, for some Latin American Countries in our sample, the magnitude of gender labor gaps in four dimensions: participation, wages, high skilled employment, and top job gaps. All figures also show the same gap for three developed countries (the United States, Germany, and Canada), as well as the position of each country in the *GGGR* ranking (in parentheses).

Figure 1 shows the participation rate gap[17]. It is observed that, on average, female labor force participation (FLFP) rates in these Latin American countries are almost 30% lower than those of men, with Bolivia being the country with the smallest gap (20%). Moreover, developed economies are ranked in the top 50 based on participation gaps, while in Latin American countries hold positions as high as 68th and as low as 118th. Wage gaps (unconditional to observed characteristics) are shown in Figure 2[18]. Note that, on average, women earn 47% less than men: Chile and Colombia are the countries with the largest and the smallest gaps, respectively. Wage gaps place these Latin American countries among those with the largest gender disparities (they rank between 106th and 128th of 142 countries), clearly positioning them behind the developed world.

Figure 3 shows that, in this group of Latin American countries, results are mixed regarding gender gaps related to access to high skill jobs (professional and technical workers)[19]. Indeed, in some countries, like Peru and Mexico, the employment rate for women in these types of jobs is more than 20% lower than that for men; in contrast, in countries like Uruguay, the gap is in women's favor. Also, it is worth mentioning that, in the developed world, job segmentation by skill level is either close to zero or even in women's favor. Finally, Figure 4 shows employment rates in top jobs (managers, senior officials, and legislators). These descriptive data support the glass ceiling hypothesis: with the exception of Colombia, the employment rate in these jobs is between 22% and 69% lower for women than for men. These results are more in line with those observed in the developed countries considered for comparison purposes (Canada, USA, and Germany). To sum up, gaps in participation and wages in Latin American countries are large, while women appear to be segregated in

[17] This is the ratio between the participation rates of female and male workers.

[18] This is the ratio between the average wages of female and male workers.

[19] This is the ratio between the proportion of female workers in a particular type of job and their male counterparts.

low-skilled and non-top jobs.

There is a vast literature on gender wage disparity in Latin America aimed at assessing whether wage gaps can be explained by observables and unobservables, using either the traditional Blinder-Oaxaca decomposition technique or more generalized approaches such as those suggested by Machado and Mata (2005) and Melly (2005) or more recently by Ñopo (2008)[20]. However, few papers[21] have studied study wage gaps using harmonized data in the region. Carrillo et al. (2014) and Atal et al. (2010) are two more recent examples. Carrillo et al. (2014), following Firpo et al. (2009), use quantile regressions to decompose gender wage gaps in twelve countries, finding a substantial unexplained gender gap in the extremes of the wage distribution. There is high heterogeneity in the sample. The magnitude of these gaps at the top and bottom of the wage distribution is highly correlated with GDP and income inequality. Atal et al. (2010), using data from eighteen countries, finds that men's wages are 10% higher than those of women in the whole region, but if women were equal to men (in terms of observables), the wage gap would jump to 20%. The authors find substantial inter-country heterogeneity both in the raw gaps and in the unexplained gender gaps and, contrary to conventional wisdom, report that wage gaps are larger for self-employed workers.

3.2 Data

In this paper, we use data from household surveys and employment surveys conducted in nine Latin American countries (see Table 1 for a description of the data and their sources). The data have been homogenized in order to recover information on wages, gender, (ongoing) unemployment duration, age, education, and employment status. All data sets are representative at the national level. The analysis will be focused on men and women between 25 and 55 years old. Data on wages is obtained from the individuals' primary occupation only, and hourly wages are estimated using reported working hours for this occupation and expressed in constant PPP US dollars of December 2013. The reasons for studying wage differentials among wage earners only are twofold. First, self reported data on wages for self-employed workers is typically very noisy and affected by measurement errors; second, and more importantly, it is difficult to rationalize the idea of employer discrimination in a self-employment context. Table 2 shows that 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%. Note that, in the theoretical model, self-employment is

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

[21] Most studies are country-specific. See for example Arceo-Gómez and Campos-Vázquez (2014) for Mexico, Badel and Peña (2010) for Colombia, and Borraz and Robano (2010) for Uruguay, among others. Atal et al. (2010) provides a comprehensive review.

a valid employment state, but the model does not distinguish between formal and informal wage earners in the data. 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 3 presents descriptive statistics by country and gender. There is a huge inter-country heterogeneity in unemployment durations and unemployment rates. Countries like Chile, Mexico, and Peru display the shortest (ongoing) unemployment durations, while Uruguay, Bolivia, and Paraguay have the longest. Unemployment durations are higher for women, except in Mexico and Peru, where this relationship is reversed. The largest gaps in unemployment durations by gender is found in Bolivia and Paraguay, while the smallest gaps are found 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 found 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 found in Uruguay, Bolivia, and Mexico. In all countries, except for Colombia, men's wage distributions show a higher relative dispersion (measured using the coefficient of variation) than women's. Chile displays the highest relative wage dispersion for both women and men.

3.3 Estimation Results

Table 4 presents the estimated parameters. For all countries, except Colombia, the model with full heterogeneity in the parameters of the labor market by gender and with the presence of prejudice is supported by the data. For Colombia, the best model does not include prejudice. In terms of the estimated parameters, the main findings are five-fold. First, rows one and two of table 4 show the estimates of the Poisson rate at which workers meet potential employers (or the rate at which job offers arrive). 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 three countries, 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.

Second, rows three and four of table 4 show the estimates of the Poisson rate at which involuntary separation shocks occur, which conveys information on the average duration of a job. 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 and this holds regardless of gender. In these countries, jobs last between 11 and 22 years and between 8 and 33 years for men and women, respectively. At the other end of the spectrum, 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, in Colombia and Peru, job durations for men almost double job durations for women. In Chile, Mexico, and Uruguay, gender differences are smaller.

Third, rows five to eight of table 4 show the location and the scale parameters of the productivity distributions by gender. Given the log-normality assumption, the average productivity implied in those estimates is shown by gender in the second row of the top and mid panels of table 5[22]. In five out of nine countries, average productivity is higher for men than for women, with Chile and Ecuador being the countries where a greater difference can be observed (36% and 20% respectively); in Colombia, Paraguay, and Peru, productivity gaps between men and women (although in men's favor) are smaller (around 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.

Fourth, rows nine and ten show the estimates of the intensity of discrimination and the proportion of prejudiced employers. It is important to mention that the intensity of discrimination is not directly comparable across countries and skill levels because workers have different productivities 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, $E[x|M]$. Figure 5 shows this measure of relative intensity and the proportion of total workers whose employer is prejudiced, graphically summarizing (comparable) information related to rows nine and ten of table 4. It is important to make two comments regarding figure 5. 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 25-30% in Argentina, Uruguay, and Bolivia, and around 15% in Paraguay and Peru. Second, countries in our sample are highly similar regarding the proportion of prejudiced employers. The country with the lowest proportion is Peru (38%), while the highest rate is observed in Paraguay (almost 43%). Note that, for Colombia, the existence of prejudiced employers for skilled workers is rejected.

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

Rows eleven and twelve of table 4 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 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%). Finally, rows thirteen to sixteen of table 4 show the estimated parameters of distributions $Q(z)$ and $R(y)$.

Regarding the goodness of fit of the model, table 5 presents the model predictions predictions for several measures. The comparison of these predictions to the descriptive statistics provided in Table 3 shows that the overall fit of the model is very good for all countries.

3.4 Sources of Gender Gaps

In order to analyze the effect of each potential source on gender gaps, we performed 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 wage distribution. We also computed gaps in unemployment, employment, self-employment, and participation rates. All equilibrium effects are considered in our computations. The first experiment (called Productivity) analyzed how important productivity differences are by equalizing the parameters that characterize the productivity distribution μ and σ between women and men (the point estimates for men are used). All the remaining parameters were set at their point estimates. The second experiment (called Prejudice) analyzed the role of discrimination intensity and the proportion of prejudiced employers in gender gaps. In this experiment, d and p were set at zero. The last experiment (called Transitions) analyzed the role of gender differences in labor market dynamics. In this case, the arrival rates of jobs and involuntary separations were set at the point estimates for men. Finally, in the fourth experiment (Non-market value), differences in the distribution of non-market values between men and women are turned off, setting the non-market value distribution for women at a level equal to that of men.

The gap (women's outcome relative to men's) that each experiment generates[23] is presented in the first four rows assigned to each country in Table 6. Additionally, for comparison purposes, row 5 presents the gaps generated by the model, with all parameters set at their point estimates (row labeled All Parameters in the table), and row 6 shows the wage gap observed in the data (row labeled Data in the table). Column 1 presents the mean wage gap, while columns 2 and 3 present wage gaps at the bottom and top quartiles (25%) of

[23]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.

the wage distribution. Columns 4 to 7 present the predicted gaps in all states of the labor market. Figure 6 shows changes in gender ratios for participation, employment, and wages, to emphasize how much (in percentage points) the women/men ratio would increase (thus reducing the wage gap) in each scenario relative to the ratios predicted by the model and those observed in the data (as benchmarks)[24].

Several general facts emerge from table 6. First, the model with all estimated parameters adequately replicates the observed gender wage and participation, employment, unemployment, and self-employment gaps. In the particular case of wages, this is observed both in the average and at the top and bottom of the wage distribution. Second, in three countries, Argentina, Bolivia, and Uruguay, the overall wage gap at the bottom of the distribution slightly favors women, who receive wages 1.5-2% higher than men. In the other six countries, although negative toward women, wage gaps at the bottom are much lower than at the top. Colombia is the only country where the overall wage gap is around 11-14% through the whole wage distribution. Third, in all the countries examined, except for Mexico, unemployment rates are much higher for women than for men. Employment rates are pretty similar between women and men (with the gap being at most 7%). In all the countries studied, both participation rates and self-employment rates are higher for men.

In the multiple scenarios considered in the counter-factual experiments, some patterns arise regarding wage, participation, self-employment, unemployment, and employment rate gaps (see Figure 6).

In the absence of differences in productivity between men and women, countries can be divided into two groups. The first is formed by Argentina, Bolivia, Mexico, and Uruguay, where women are more productive than men. Here, turning off productivity differences makes 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. This effect does not hold for high wage earners. In the second group, formed by 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 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.

[24]In figure 6, improvements in wage ratios are colored green, while increasing gaps (decreasing ratios) are colored red. Yellow signals situations in which gaps remain similar to the ones observed in the benchmark.

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 for Chile, higher relative participation rates in this scenario correspond with 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 to women (see Table 6). 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 to men). At the bottom quarter, gaps become favorable to 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 to women both on average (wage ratios are 1.16 and 1.08 respectively) and for the first quartile (1.54 and 1.38). At the top, the wage gap between women and men vanishes in Mexico and grows from 0.86 to 0.93 in Uruguay. In the particular case of Uruguay, wage gaps are small, but prejudice is playing 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, so, if we neutralize them, relative participation and employment rates would increase, while self-employment rates would 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 to women in this scenario. In Chile and Mexico, on the contrary, 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.

Finally, eliminating differences in non-market value between men and women substantially increases participation rates. In Argentina, Bolivia, and Paraguay, gaps in participation rates vanish, while in all remaining countries, except for Colombia and Peru, the remaining gaps drop to almost 2 percentage points (still against women). In the case of the latter two countries, the participation gaps that remain are around 4 percentage points.

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. The importance of this source varies across countries. In Argentina, Bolivia, and Uruguay, wage ratios (women/men ratio) increase by around 15% (relative to the original gap); in Ecuador, Paraguay, and Peru, the rise is closer to 10%, while in Chile and Mexico it is around 25%. 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 not such a clear pattern regarding the relative importance of productivity and labor market dynamics. In four countries, Argentina, Bolivia, Mexico, and Uruguay, women are on average more productive than men; therefore, turning off productivity differences increases wage gaps on average and for low wage earners. For high wage earners, turning off productivity differences does reduce wage gaps by 5 to 10 percentage points (depending on the country). In Colombia, Ecuador, and Paraguay, turning off productivity differences equalizes wages between women and men across the whole wage distribution. In Peru, the contribution of this source to the overall wage gap is smaller, but more important for high wage earners. Finally, in Chile, women's productivities are very low relative to men's; so, if they were equally productive, women would earn 40% more than men on average, but would double men's wages at the bottom quartile. Labor market dynamics favor skilled women in only two out of nine countries (Chile and Mexico)[25], play a minor role in Uruguay, and hurt women in the the remaining six countries. Once again, larger effects are found at the bottom of the distribution. Finally, in all countries, non-market values are important for explaining participation rate gaps.

3.5 Policy experiments: hiring subsidy and equal-pay policies

We used the model to analyze the potential impact of two different labor market policies aimed at mitigating gender gaps: a hiring subsidy (defined as 10% of the estimated d) and an equal-pay policy. In the first case, a subsidy is offered to prejudiced employers. In the second, a law is passed, forcing all employers to pay equal wages to both women and men. The wage rate in this case is defined as a weighted average of the bargained wage rate of men and women. In both cases, we measure the impact of the policy on worker's welfare and other labor market outcomes such as wages, unemployment durations, and labor market participation, among others. Results are presented in Table 7. 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

[25]Flabbi (2010b) also finds a similar result for skilled women in the US. In these two countries, gender differences in labor market transitions close the gap, which could be as large as 40% in Chile and 20% in Mexico if we shut down differences from this source.

wages, unemployment, self-employment and participation rates, unemployment duration, and average wages.[26] As expected, women achieve a lower 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 prejudiced 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, where the policy generates a 26% gap in favor of women. 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. Still, the policy does affect reservation wages and self-employment rates. In all the countries studied, women's reservation wages increase relative to men's, while relative self-employment rates plummet. The maximum effect is found in Chile and Mexico, two countries 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. It is worth noticing that, 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), followed by Argentina, Bolivia, Peru, and Uruguay, where men's welfare falls by 11 to 13 percentage points. 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 points) and the smallest in Colombia (3 percentage points). In Argentina, Bolivia, Chile, and Uruguay, the impact on wages is also high (8-11 percentage points). In all these countries, except for Chile, wage gaps in this scenario are favorable to 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

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

(relative) unemployment for women. Reservation wages ratios increase, almost doubling in Chile and Mexico.

To sum up, both policies generate convergence in wages, but the largest reduction (which in fact 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, the countries in which women's wages improve the most are Mexico, 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.

4 Final Remarks

In this paper, a search model of the labor market with participation decisions, occupational choice, search frictions, match-specific heterogeneity, and taste discrimination is estimated for nine Latin American countries in order to separate the impact of pure discrimination 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, except for Colombia, the fully flexible 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 structure makes it possible to characterize these countries in terms of job mobility, average productivity, and prejudice. The country with the highest mobility rates is by far Peru (with a high arrival rate of job offers and a high separation rate), followed by Chile and Mexico, while those with the lowest mobility levels are Argentina, Bolivia, and Uruguay. There are huge differences in productivity by gender, with the largest gaps being found in Chile and Ecuador. In terms of prejudice, relative intensity ranges from 0.12 in Ecuador to almost 0.40 in Mexico and Chile. The proportion of the labor force working with prejudiced employers lies between 37 and 42% for all countries.

Wage gap levels display high inter-country heterogeneity, but it is worth pointing out that wage gaps are larger at the top of the distribution. In all countries, wage gaps are favorable to men on average. The smallest wage gap is found in Argentina (where women earn 4% less than men), while the largest is found in Chile (almost 30%). At the bottom of the wage distribution, women earn as much as men in three countries (Argentina, Bolivia, and

Uruguay), while in Paraguay, Colombia, Ecuador, Peru, and Mexico wage gaps range from 3% (in Paraguay) to almost 10% (in Peru). At the top of the wage distribution, in all the countries the wage gap is favorable to men, the largest wage gap is found in Chile (32.5%), followed by Ecuador (26.6%) and Paraguay (21.5%). In the rest of the countries, the wage gap at the top quartile ranges between 9% and 16%.

In each of the countries studied, it is possible to determine the importance of the multiple sources of wage differentials. In Bolivia, Colombia, Paraguay, and Peru, the main source of wage gaps is labor market dynamics; in Chile and Ecuador, productivity differences (closely followed by prejudice); and, in Mexico and Uruguay, prejudice. Finally, in Argentina, both labor market dynamics and prejudice are equally important in explaining wage gaps.

Note that, contrary to what has been reported in the literature, prejudice is not necessarily the main force behind gender wage gaps in Latin American countries. Wage gaps are sizable and strongly influenced by prejudice in two countries, Mexico and Chile. In Uruguay and Argentina, where wage gaps are smaller in the first place, prejudice is also an important source of gender wage differentials. Overall, prejudice has a huge impact on gender wage gaps among low-wage earners, but plays a minor role at the top.

Other patterns also arise. In four countries (Argentina, Bolivia, Mexico, and Uruguay), productivity differences favor women, generating more beneficial wage gaps on average and at the bottom of the distribution. In the rest of the sample (Chile, Colombia, Ecuador, Peru, and Paraguay), productivity differences always generate gaps in favor of men. In Ecuador and Colombia, this effect is present with similar intensity along the whole wage distribution. In Paraguay and Peru, productivity differences matter mostly for high wage earners, while in Chile the strongest effect is found at the first quartile. In six out of nine countries, labor market dynamics generate large wage gaps on average (around 10-15%), but much larger gaps for low wage earners (30-40%). The exceptions are Uruguay, Chile, and Mexico. In Uruguay, wage differences due to labor dynamics are small. In Chile and Mexico, labor market dynamics favor women; so, in a scenario of equal labor dynamics, wage gaps increase particularly for low wage earners. In these two countries, differences in labor market transitions favor women, reducing wage, participation, and employment gaps.

We analyze the potential effects of two different policies: a hiring subsidy and an equal-pay policy, finding that the former is far more effective for reducing wage gaps. The most dramatic effects of this policy are found in Argentina, Bolivia, Mexico, and Uruguay.

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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: Formal Workers and Wage Earners

	ARG	BOL	CHL	COL	ECU	MEX	PAR	PER	URU
Formal Employees/(Formal Employees + Informal Employees)(*)									
Men	90.3%	91.0%	95.1%	93.5%	94.0%	88.1%	84.9%	88.1%	97.0%
Women	89.9%	90.1%	94.0%	92.8%	94.0%	88.9%	86.1%	89.5%	97.2%
Employees/(Employees + Self Employed Workers)									
Men	82.2%	80.2%	87.5%	67.0%	82.4%	86.2%	84.7%	80.2%	77.1%
Women	88.2%	81.0%	91.0%	70.4%	89.2%	88.5%	88.5%	80.6%	82.6%

(*) In all countries, except Ecuador and Uruguay, a formal employee is defined as a worker with an explicit job contract. In Ecuador and Uruguay, contributions to the social security system are used to define formal employees.

Table 3: Descriptive Statistics

Country	N	$Pr(U)$	$Pr(E)$	$Pr(SE)$	$Pr(P)$	$E(w\|E)$	$SD(w\|E)$	$E(t\|U)$	$SD(t\|U)$
					Men				
Argentina	2376	0.024	0.793	0.183	0.974	12.61	6.64	-	-
Bolivia	1969	0.024	0.777	0.199	0.940	7.21	5.08	5.36	5.82
Chile	6628	0.049	0.823	0.128	0.954	15.34	13.02	2.95	3.61
Colombia	2604	0.084	0.589	0.327	0.964	6.84	4.79	4.75	5.59
Ecuador	2260	0.024	0.798	0.178	0.981	9.36	6.12	4.00	3.95
Mexico	11039	0.064	0.747	0.189	0.935	7.42	4.89	3.07	3.76
Paraguay	1587	0.018	0.827	0.155	0.970	9.93	6.38	5.63	5.58
Peru	3898	0.032	0.762	0.206	0.960	7.69	5.94	1.01	1.38
Uruguay	5245	0.022	0.753	0.225	0.980	10.31	7.71	7.36	6.74
					Women				
Argentina	4013	0.034	0.839	0.127	0.882	12.15	5.58	-	-
Bolivia	1867	0.027	0.785	0.189	0.821	6.75	3.79	12.11	11.79
Chile	8190	0.057	0.852	0.091	0.837	11.06	8.69	3.04	3.92
Colombia	3895	0.139	0.590	0.271	0.856	6.16	4.35	4.86	6.13
Ecuador	3096	0.038	0.853	0.109	0.869	7.58	3.96	4.46	3.98
Mexico	16675	0.058	0.790	0.153	0.671	6.89	4.22	2.97	3.60
Paraguay	2380	0.021	0.863	0.116	0.903	8.60	4.53	10.03	8.10
Peru	4354	0.053	0.747	0.200	0.838	6.80	4.79	0.96	0.89
Uruguay	8137	0.028	0.802	0.170	0.909	9.57	5.59	7.69	6.32
					Women / Men				
Argentina	-	1.41	1.06	0.69	0.91	0.96	0.84	-	-
Bolivia	-	1.12	1.01	0.95	0.87	0.94	0.75	2.26	2.02
Chile	-	1.17	1.04	0.71	0.88	0.72	0.67	1.03	1.08
Colombia	-	1.66	1.00	0.83	0.89	0.90	0.91	1.02	1.10
Ecuador	-	1.60	1.07	0.61	0.89	0.81	0.65	1.12	1.01
Mexico	-	0.90	1.06	0.81	0.72	0.93	0.86	0.97	0.96
Paraguay	-	1.18	1.04	0.74	0.93	0.87	0.71	1.78	1.45
Peru	-	1.69	0.98	0.97	0.87	0.88	0.81	0.95	0.65
Uruguay	-	1.27	1.07	0.75	0.93	0.93	0.72	1.05	0.94

Note: Duration data in Argentina is defined qualitatively.

Table 4: Estimated Parameters

Param.	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	-	1.9995	5.2041	2.9149	1.9167	4.2610
	(0.0016)	(1.8056)	(0.3178)	-	(0.0531)	(0.0035)	(0.0199)	(1.8911)	(0.8744)
p	0.4988	0.4992	0.4964	-	0.4995	0.4976	0.4995	0.5000	0.4989
	(0.0859)	(0.3740)	(0.9518)	-	(0.5071)	(0.0301)	(0.2945)	(0.6722)	(0.1809)
w^*_M	3.64612	1.7512	3.2054	2.1018	2.7406	1.7238	2.8119	1.8280	2.3525
w^*_W	3.592742	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
N	4862	2663	11471	4037	4119	17433	3125	5755	9878
lnL	-15195.101	-7315	-39289	-12009	-11660	-50164	-9039	-16067	-30488
LR Test	82	18	24	0	6	142	9	15	97

Note: Asymptotic standard errors in parentheses.

Table 5: 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 6: Counter-factual Experiments

Counter-factual	Wages			Labor Market States			
	Entire Distribution	Bottom 25%	Top 25%	$Pr(U)$	$Pr(E)$	$Pr(SE)$	$Pr(P)$
Argentina							
Closing Gaps in:							
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
Non Market Value	0.958	1.017	0.889	1.412	1.058	0.694	0.994
All Parameters	0.958	1.017	0.889	1.412	1.058	0.694	0.906
Data	0.963	1.002	0.896	1.412	1.058	0.694	0.906
Bolivia							
Closing Gaps in:							
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
Non Market Value	0.936	1.015	0.865	1.125	1.009	0.948	1.001
All Parameters	0.936	1.015	0.865	1.125	1.009	0.948	0.873
Data	0.936	1.009	0.876	1.125	1.009	0.948	0.873
Chile							
Closing Gaps in:							
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
Non Market Value	0.714	0.811	0.668	1.175	1.035	0.705	0.983
All Parameters	0.714	0.811	0.668	1.175	1.035	0.705	0.877
Data	0.721	0.808	0.675	1.175	1.036	0.705	0.877
Colombia							
Closing Gaps in:							
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
Non Market Value	0.887	0.892	0.863	1.654	1.000	0.829	0.953
All Parameters	0.887	0.892	0.863	1.654	1.000	0.829	0.888
Data	0.900	0.924	0.914	1.656	1.002	0.829	0.888
Ecuador							
Closing Gaps in:							
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
Non Market Value	0.810	0.919	0.739	1.601	1.068	0.613	0.987
All Parameters	0.810	0.919	0.739	1.601	1.068	0.613	0.886
Data	0.810	0.912	0.734	1.602	1.068	0.613	0.886

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Table 6: Counter-factual Experiments – continued from previous page

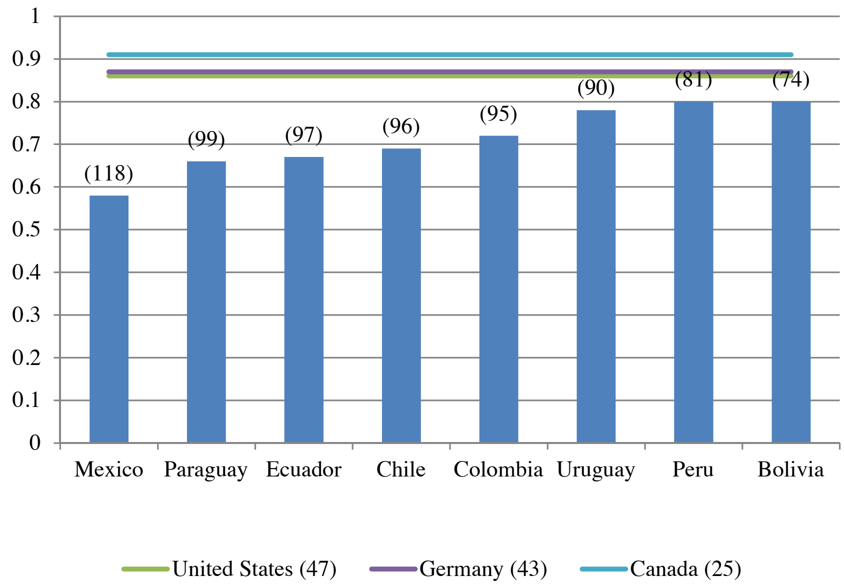
Counter-factual	Wages			Labor Market States			
	Entire Distribution	Bottom 25%	Top 25%	$Pr(U)$	$Pr(E)$	$Pr(SE)$	$Pr(P)$
				Mexico			
Closing Gaps in:							
Productivity	0.906	0.767	0.958	0.873	0.971	1.160	0.655
Prejudice	1.156	1.542	0.994	0.968	1.226	0.120	0.936
Transitions	0.818	0.640	0.829	0.552	0.525	3.024	0.493
Non Market Value	0.922	0.941	0.878	0.904	1.058	0.806	0.988
All Parameters	0.922	0.941	0.878	0.904	1.058	0.806	0.717
Data	0.929	0.945	0.902	0.904	1.058	0.806	0.717
				Paraguay			
Closing Gaps in:							
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
Non Market Value	0.866	0.977	0.792	1.178	1.044	0.744	0.996
All Parameters	0.866	0.977	0.792	1.178	1.044	0.744	0.930
Data	0.866	0.967	0.785	1.178	1.044	0.744	0.930
				Peru			
Closing Gaps in:							
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
Non Market Value	0.882	0.906	0.844	1.685	0.980	0.967	0.955
All Parameters	0.882	0.906	0.844	1.685	0.980	0.967	0.873
Data	0.884	0.905	0.845	1.686	0.980	0.967	0.873
				Uruguay			
Closing Gaps in:							
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
Non Market Value	0.934	1.021	0.857	1.267	1.066	0.754	0.988
All Parameters	0.934	1.021	0.857	1.267	1.066	0.754	0.928
Data	0.929	1.006	0.837	1.268	1.066	0.754	0.928

Table 7: 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

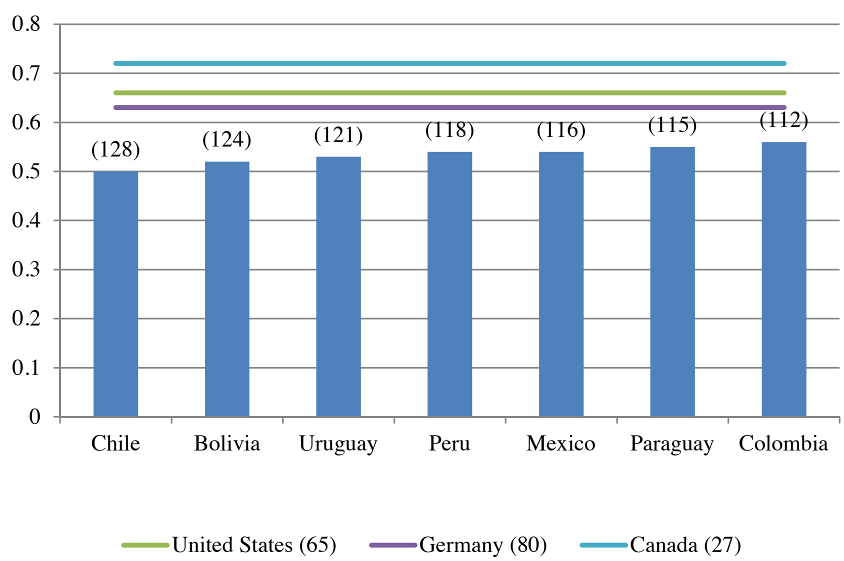
Note: All welfare measures are relative to those of men in the base model.

Figure 1: Participation Rate Gaps (Female / Male)



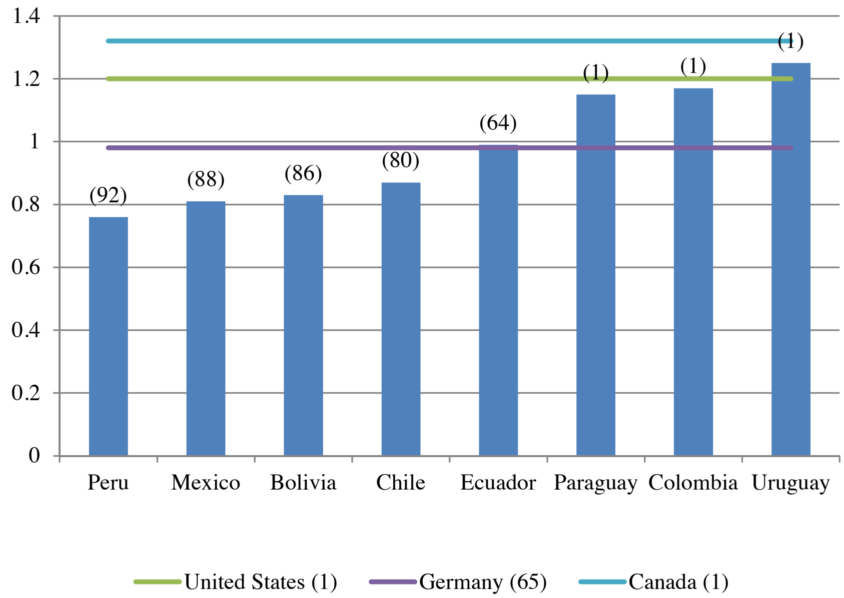
Note: 2014 Global Gender Gap Report rankings in parentheses.

Figure 2: Wage Gaps (Female / Male)



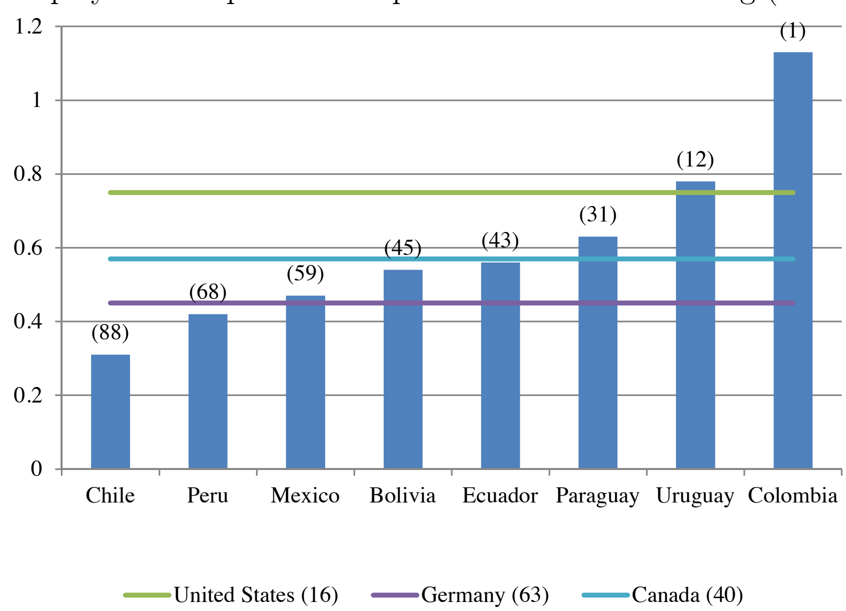
Note: 2014 Global Gender Gap Report rankings in parentheses.

Figure 3: Employment Gaps in Jobs for High Skilled Workers (Female / Male)



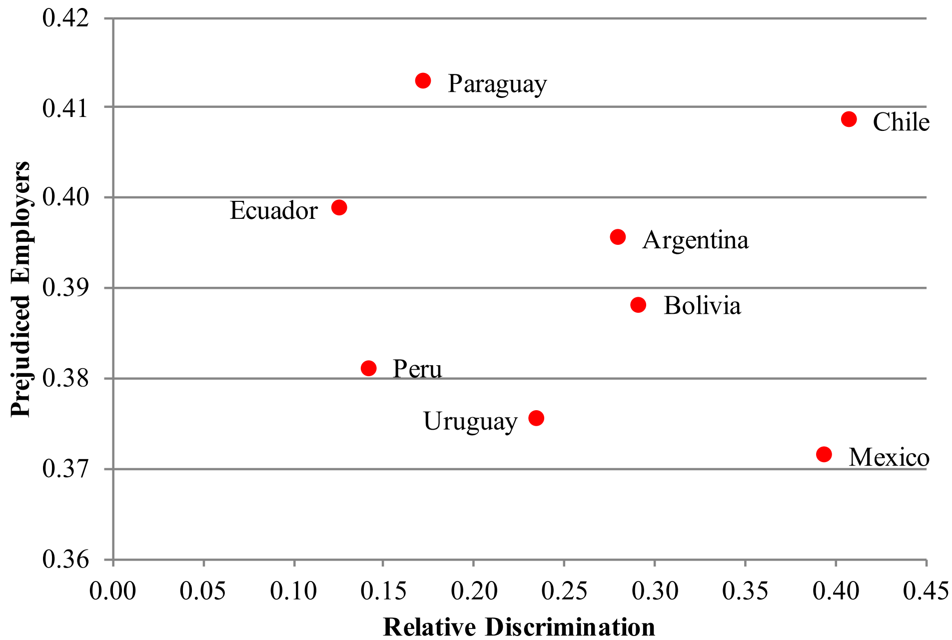
Note: 2014 Global Gender Gap Report rankings in parentheses.

Figure 4: Employment Gaps in the Top Jobs - The Glass Ceiling (Female / Male)



Note: 2014 Global Gender Gap Report rankings in parentheses.

Figure 5: Cross-Country Comparison of Discrimination Intensity



Note: The proportion of prejudiced employers is presented conditional on wage jobs ($p\Pr[E]$), while discrimination intensity is presented relative to the average productivity of men (that is, $d/E[x|M]$).

Figure 6: Changes in Labor Market Outcomes under Different Counter-factual Scenarios

		AR	BOL	CHI	COL	ECU	MEX	PAY	PER	URY
In the absence of Preductivity Differences	Participation	-0.04	-0.02	0.17	0.04	0.08	-0.06	0.03	0.06	-0.03
	Employment	-0.07	-0.04	0.09	0.08	0.09	-0.09	0.04	0.09	-0.07
	Average wage	-0.07	0.00	0.65	0.11	0.25	-0.02	0.13	0.09	-0.02
	Low-wage earners	-0.24	-0.16	1.16	0.10	0.24	-0.17	0.04	0.03	-0.23
	High-wage earners	0.05	0.10	0.55	0.14	0.29	0.08	0.21	0.14	0.10
In the absence of Prejudice	Participation	0.05	0.06	0.14	0.00	0.04	0.22	0.03	0.09	0.06
	Employment	0.07	0.10	0.11	0.00	0.05	0.17	0.04	0.14	0.13
	Average wage	0.15	0.14	0.19	0.00	0.07	0.23	0.08	0.10	0.14
	Low-wage earners	0.34	0.34	0.58	0.00	0.16	0.60	0.19	0.26	0.36
	High-wage earners	0.08	0.07	0.08	0.00	0.04	0.12	0.04	0.05	0.07
In the absence of labor transitions differences	Participation	0.10	0.17	-0.25	0.09	0.05	-0.22	0.08	0.14	0.02
	Employment	0.14	0.21	-0.41	0.32	0.07	-0.53	0.11	0.24	0.05
	Average wage	0.14	0.25	-0.10	0.15	0.05	-0.10	0.16	0.15	0.02
	Low-wage earners	0.33	0.67	-0.32	0.39	0.12	-0.30	0.41	0.43	0.04
	High-wage earners	0.07	0.12	-0.05	0.08	0.02	-0.05	0.08	0.07	0.01