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ABSTRACT

Gender Gaps in Latin American Labor Markets: Implications from an Estimated Search Model*

We develop and estimate a search model that captures the specific characteristics of Latin America and Caribbean (LAC) labor markets and the crucial differences between men and women. Labor force participation decisions are integrated in the labor market dynamics, taking into account sample selection over unobservables. The model is estimated on four LAC countries (Argentina, Chile, Colombia and Mexico) and on three education levels (Primary, Secondary and Tertiary). We use the estimated model to study changes in gender gaps and in output implied by policies that increase the labor force participation of women. We focus on four policies: an increase in the provision of child care, an increase in average female productivity, a gender-based contribution rate for formal employees, and changes in formality and informality costs. We find that the impact on the extensive margin of the female labor supply is the main channel responsible for the policy-induced increase in output.

JEL Classification: J24, J3, J64, O17

Keywords: gender gaps, female labor force participation, labor market frictions, search and matching, Nash bargaining, informality

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* The findings, interpretations, and conclusions expressed in this paper are those of the authors and do not necessarily represent the views of the Inter-American Development Bank, its Executive Directors, or the governments they represent.

1 Introduction

The labor force participation of women is lower than the labor force participation of men. This empirical regularity is found in virtually all countries[1] and it holds true in Latin America and the Caribbeans (LAC). For example, Busso and Fonseca (2015) show that average female labor force participation in LAC in 2010 was about 65% compared to about 76% in the US. There are important differences between LAC countries, with values ranging from the mid 50% of Honduras and Mexico to the high 70% of Peru and Uruguay. At the same time, when women do participate in the labor market, they earn on average lower wages, work on average less hours, face more job instability and have on average less career progression. These differences are frequently labeled the 'gender gap in the labor market' and are significant in most LAC countries with the possible exception of some Caribbean countries.[2]

In terms of labor market productivity and growth potential – quite crucial in middle- and low-income countries such as those in LAC – these lower participation rates constitute a reserve of untapped resources. The potential positive impact of bringing more women to the labor market has been increasing over time since women are acquiring more and more human capital with each passing generation.[3]

In this paper we provide estimates of changes in gender gaps in the labor market and in overall and per-capita output implied by policies that increase the labor force participation of women. We evaluate these policies within an estimated model able to take into account the different workers' behavior implied by the policies, at least with respect to participation decisions and job search and acceptance decisions.

The model we develop and estimate is a search model of the labor market which captures the specific characteristics of LAC labor markets, including the high level of informality and self-employment. Labor force participation decisions are integrated in the labor market dynamics, taking into account sample selection because the optimal decisions implemented by the agents are sensitive to the policy parameters.

[1] See for example Blau and Kahn (2013) showing gender difference in employment rates in a large sample of high-income countries or Olivetti and Petrongolo (2008) showing gender difference in participation rates in a large sample of OECD countries. On average, participation rates for men are about 90% while participation rates for women are about 75%.

[2] Empirical contributions discussing gender gaps in wages include Carrillo et al. (2014); WorldBank (2012); in job instability, WorldBank (2012); in career progression, Abrahams et al. (2017).

[3] For example, schooling completed among women is now higher than men in all high income economies and in many LAC economies. Argentina, Brazil, Colombia, Uruguay: all report a positive gender gap in years of schooling completed, i.e. women have on average more years of schooling completed than men. The aggregate average for LAC in 2012 is a small positive gender gap in favor of women contrasting with a half year of negative gap in 1992 (Marchionni, 2015).

Search models of the labor market are widespread and influential[4] since they introduce labor market dynamic, equilibrium unemployment and non-competitive features in a tractable and empirically relevant model of the market. Their use to answer policy questions using micro-data has a long tradition.[5] In order to adapt this approach to labor markets in LAC, it is important to consider the variety of labor market states present in the region.[6] We model the large informal sector as composed by self-employed and informal employees but we keep them in separate labor market states in order to capture the systematic differences in their observed labor market dynamics. Individuals are allowed to move optimally between labor market states and may choose to do so as a result of shocks and new opportunities.

An additional step is needed to adapt the framework to the study of female labor force participation: a labor supply decision. We introduce an endogenous participation decision as a function of individual heterogeneity over out-of-labor-market utility. The utility is allowed to vary by the observable characteristic which is considered the most important in determining its value: the presence of young children in the household.

Finally, we add to the model measures able to capture the potential impact on output and aggregate welfare. We accomplish this by introducing a match-specific productivity distribution which is affected by policy variables and by optimal individual behavior. This approach dates back to at least Eckstein and Wolpin (1995). In the gender literature, it has been used by Flabbi (2010a) to evaluate affirmative action policies in favor of women. In the gender literature in LAC, it has been used by Perticara and Tejada (2016) to estimate the presence of discrimination against women focusing on formal jobs and in the college graduates market.

Following the approach suggested by Jolivet et al. (2006), we keep the model particularly parsimonious since we want to estimate the same model on a variety of countries and schooling levels. We are able to estimate the model on four large LAC countries (Argentina, Chile, Colombia and Mexico) and on three education levels (Primary, Secondary and Tertiary). The estimated parameters are generally precise and the fit quite good. They imply some novel results, such as the difference between the gender gap computed on wages and the one

[4]For a survey of the theoretical literature, see Rogerson et al. (2005). For a survey of the empirical literature, see Eckstein and van den Berg (2007).

[5]For example, Eckstein and Wolpin (1995) study returns to schooling; Ahn et al. (2011) and Flinn (2006) evaluate the employment and welfare impact of minimum wage legislation; Dey and Flinn (2005) the impact of employer-provided health insurance; Flabbi (2010a) the effect of affirmative action legislation; and Cahuc et al. (2006) the impact of workers' bargaining power.

[6]Recent contributions using this approach to answer policy questions in LAC include: Tejada (2017) focusing on the distortions of introducing multiple labor contracts; Bobba et al. (2017) assessing the effect of non-contributory benefits, informality and long-term impacts on education; and Meghir et al. (2015) studying the impact of tightening enforcement.

based on productivity.

We use the estimated model to perform a variety of policy experiments, evaluating their impact on labor market outcomes and output, decomposing the direct effects and the equilibrium effects. The main conclusion is that the impact on the extensive margin of the female labor supply is a very important channel in generating the output increase produced by some of our policies.

The paper is organized as follows. Section 2 presents the model. Section 3 provides a description of the data used in estimation. Section 4 presents the estimation method and the main identification strategy. More details on the identification are given in Appendix D. Section 5 presents the main estimation results. Complete results are available in Appendix E. Section 6 defines, presents and discusses the policy experiments. Additional results on the experiments are available in Appendix E. Section 7 concludes.

2 Model

We propose a search model of the labor market able to capture the specific characteristics of LAC labor markets and to account for the endogenous labor supply decisions of women. To this end, we allow informality to be described by two labor market states: informal employee and self-employment. Frequently, employees hired informally and the self-employed are grouped together in the category informal work (see for example Meghir et al., 2015). However, contributions more attuned to the institutional details of the region – such as Anton et al. (2012) and Bobba et al. (2017) – suggest that differentiating the informal sectors in these two distinct labor market states constitutes a better description of LAC labor markets. To adapt the framework to the study of female labor force participation, we add a labor supply decision. Women endogenous participation decision is a function of their specific utility in out-of-labor-market activities. The out-of-labor-market utility is allowed to change if young children are present in the household. We limit the labor supply decision to the extensive margin without modeling the intensive margin due to data limitations. While contributions exist that consider both margins of the labor supply decision using similar models,[7] we do not observe much about the features of either the workers' side or the firms' side heterogeneity that induces differences in the intensive margin decision. But we will be able to use wages per hour to estimate the structural parameters of the models so as to normalize for the differences in hours worked.

[7]See for example Flabbi and Mabli (2018) for the US; and Bloemen (2008) for the Netherlands.

2.1 Environment

The specific modeling environment we start with is the so called *search-matching-bargaining* model (Eckstein and van den Berg, 2007). It is an environment characterized by search frictions, match-specific productivity and bargaining to determine wages. Crucial assumptions are stationarity, continuous time and infinitely lived individuals (or individual facing a constant death rate). In the specific model we develop in the paper, there are two types of workers: men and women, indexed by $i = M, W$. There are five, mutually exclusive states in which each worker may be in any given point in time: Non participation (NP_i), unemployment (U_i), formal employment (E_{iF}), informal employment (E_{iI}), and self-employment (E_{iS}). We denote employment states with the index $j = F, I, S$.

When non-participating, workers receive a flow utility z which is potentially different for each agent in the economy.[8] We model it as a draw z from the distribution $Q_i(z)$. When unemployed, and only then, workers can search for a job and receive job offers. While searching for a job, workers receive a flow (dis)utility b_i. Job opportunities arrive at a gender- and employment-type specific Poisson rate λ_{ij}. If a job is accepted, subsequent job termination is possible and exogenous. Termination shocks arrive at a gender- and employment-type specific Poisson rate δ_{ij}.

A job opportunity is characterized by a match-specific productivity x where $x \sim G_{ij}(x)$. The flow pay for employees is $w_{ij}(x)$ where w_{ij} is a gender- and labor relation-specific wage schedule which is determined by bargaining. The flow pay for self-employed is the full productivity x. Flow utility is linear in income. Formal jobs are subject to a payroll social security contribution, collected at the proportional rate τ and withdrawn at the source by firms.[9] Informal jobs do not pay social security contribution but they face the risk of paying a penalty if the firm is audited. Following the institutional context of the countries under consideration, the penalty has to be paid by the firm. We model it as as a constant flow cost c. The cost includes both the penalty that the firm has to pay and the probability that the auditing occurs. We do not have enough information in the data to separately identify these two components and therefore we assume this extremely parsimonious specification.

[8]This approach follows the seminal Albrecht and Axell (1984). For empirical implementations in the context of High-Income countries, see Bowlus (1997) and Flabbi (2010b).

[9]Note that we do not take into account the redistribution of this collected contributions within our model: they are therefore sunk costs. In other words, we assume that formal and informal workers receive the same social security benefits and therefore we can ignore them in the model. This assumption is motivated both by data limitations that prevent us from observing the benefits and by an institutional context where the differential in social security benefits between most formal and informal workers have been decreasing over time (Levy, 2008; Frolich et al., eds, 2014; Bobba et al., 2017).

The future is discounted at a rate ρ common to all the agents in the economy.

2.2 Value Functions

The stationarity of the environment allows for a recursive characterization of the dynamic and for a compact definition of the value function in each state.

The value of a non-participating agent of type i is:

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

It is the simplest state since a non-participating agents receives flow utility z forever.

The value of an unemployed worker of type i is as follows:

$$\begin{aligned}\rho U_i &= b_i + \lambda_{iF} \int \max\left[E_{iF}(x), U_i\right] dG_{iF}(x) + \lambda_{iI} \int \max\left[E_{iI}(x), U_i\right] dG_{iI}(x) \\ &\quad + \lambda_{iS} \int \max\left[E_{iS}(x), U_i\right] dG_{iS}(x) - (\lambda_{iF} + \lambda_{iI} + \lambda_{iS}) U_i \end{aligned} \tag{2}$$

The interpretation is intuitive. When a worker is unemployed, he receives flow utility b_i and has the possibility of meeting an employer offering a formal or an informal job with, respectively, probability λ_{iF} and λ_{iI}) or has the possibility of receiving a self-employment opportunity with probability λ_{iS}. Every time she receive a job opportunity (either as an employee or as self-employed) she can reject it or accept it, as represented by the *max* operator over the possible labor market states. The trade-off leading to the optimal decision is between accepting labor income today and continuing searching in the hope of better offers in the future. Since all future offers are realized only when meeting either a specific employer or a specific self-employment opportunity, the unemployed agent constructs expectations over the $G_{ij}(x)$ distributions.

The value of a formal employee, informal employee or self-employed of type i share a very similar structure and are as follows:

$$\rho E_{iF}(x) = w_{iF}(x) + \delta_{iF}\left[U_i - E_{iF}(x)\right] \tag{3}$$

$$\rho E_{iI}(x) = w_{iI}(x) + \delta_{iI}\left[U_i - E_{iI}(x)\right] \tag{4}$$

$$\rho E_{iS}(x) = x + \delta_{iS}\left[U_i - E_{iS}(x)\right] \tag{5}$$

Employees in a formal or an informal job receive a wage $w_{ij}(x)$ while self-employed workers receive the full production x. All jobs end exogenously at Poisson rate δ_{ij}, sending the individual to unemployment and generating a loss equal to $U_i - E_{ij}(x)$.

2.3 Wage Determination

When a worker meets an employer, the match-specific productivity of the match x is revealed to both parties. The output is shared in the usual way: the worker receives a wages and the firm keeps the profit. In our context, the flow profits are not simply productivity minus wage but they also include the specific features of the institutional context: the social security contribution τ for firms hiring formally and the illegality cost c for firms hiring informally.

The flow profits therefore are:

$$\pi_{iF}(x) = x - (1+\tau)w_{iF}(x) \tag{6}$$
$$\pi_{iI}(x) = x - w_{iI}(x) - c \tag{7}$$

Given the limited amount of information in our data, the firm side of the model is extremely stylized. Firms' values are simply represented by the flow of profits (6) and (7), discounted by the effective rate $(\rho + \delta_{ij})$.[10]

Wages are determined by bargaining. We assume the generalized axiomatic Nash bilateral bargaining outcome to solve the bargaining problem. The solution proportionally splits the total surplus of the match between employer and employee. The proportion that goes to the workers is β and it is a measure of her bargaining power together with the value of her outside option. In our case, the solution is equivalent to:

$$w_{ij} = argmax[w_{ij} - \rho U_i]^{\beta}[\pi_{ij}(x)]^{(1-\beta)} \tag{8}$$

Leading to:

$$w_{iF}(x) = \beta\frac{x}{1+\tau} + (1-\beta)\rho U_i \tag{9}$$
$$w_{iI}(x) = \beta(x-c) + (1-\beta)\rho U_i \tag{10}$$

Wages increase with the worker's productivity x. However, the productivity is decreased either by the contribution rate τ or by the illegality cost c. Moreover, the higher the worker's outside option (ρU_i), the higher the wage. Finally, the higher the worker's bargaining power β, the higher the portion of the productivity x the worker will receive through the wage.

[10]Some foundation for this specification may be given by a free-entry condition that leads the value of the vacancy to zero.

2.4 Equilibrium

The equilibrium of the model has a simple structure. Agents have to make two discrete choices. The first concerns labor market participation: either they participate in the labor market looking for a job (state U_i) or they stay out enjoying utility from out-of-labor-market activities (state NP_i). Since agents receive different utility from these activities (z), those receiving relative high utility will stay out, those receiving relative low utility will enter the market. The threshold for staying out or coming in is determined by the indifference point between the two states.

The second discrete choice the agents have to make concerns the labor market state decision: either they accept a job offer or they reject it and continue searching. Again we can identify a threshold: if the productivity and therefore the wage is high enough, they will accept; if not, they will continue searching for a better offer. As before, the threshold is identified by the indifference point between the two alternatives.

These optimal decision rules and wages schedules are then incorporated in the value of unemployment defined in equation (2), leading to the equilibrium expression (A.5) in Appendix A.

To close the steady state equilibrium, we have to impose that all inflows and outflows in and from each labor market state are equal. We do that by exploiting that the gender specific hazard rate out of unemployment to a job type j is $h_{ij} = \lambda_{ij} \left[1 - G_{ij}(x^*_{ij})\right]$ and that the hazard rate out of employment type j is exogenous and equal to δ_{ij}. The resulting equilibrium proportions are reported in equations (A.9)–(A.13) in Appendix A.

This delivers the definition of the equilibrium (Definition 1) that we report at the end of Appendix A. The model is estimated assuming the data are extracted from a steady state defined following Definition 1. Policy and counterfactual will also be performed comparing different steady state at different parameters values. In these experiments, we will use, among others, a measure representing the total output of the labor market. Specifically, we will use two measures of the aggregated average output: the output per worker (Y^{pw}) and the output per-capita (Y^{pc}). The former divides the total production by mass of workers that are currently in a job, while the latter divides the total production by the overall population, including the non-participant. We anticipate here the definitions of these two metrics. For given gender i we define:

$$
\begin{aligned}
Y_i^{pw} &= \frac{e_{iF}}{1-u_i}\int_{x_{iF}^*} x dG_{iF}(x) + \frac{e_{iI}}{1-u_i}\int_{x_{iI}^*} x dG_{iI}(x) + \frac{e_{iS}}{1-u_i}\int_{x_{iS}^*} x dG_{iS}(x) \\
Y_i^{pc} &= (1-NP_i)\left(e_{iF}\int_{x_{iF}^*} x dG_{iF}(x) + e_{iI}\int_{x_{iI}^*} x dG_{iI}(x) + e_{iS}\int_{x_{iS}^*} x dG_{iS}(x)\right)
\end{aligned}
$$

They are straightforward averages over the equilibrium measures and distributions of each labor market state in equilibrium.

3 Data

One advantage of the proposed parsimonious model is the limited data requirement, which is quite essential when trying to estimate the same model on different LAC countries and different education levels. The model can be estimated on short-panel or on cross-sectional data with limited dynamic information (durations and transitions). The minimum data requirements necessary to estimate the model are: (1) labor market status, (2) hourly wages or earnings, (3) on-going durations in the labor market state or transitions matrices between labor market states, (4) demographic characteristics, and finally (5) education or skill levels. We use data from household surveys and employment surveys from five LAC countries: Argentina, Chile, Colombia, and Mexico.[11]. To build the estimation samples, we extract all the individuals aged between 25 and 55 years old and working in non-agricultural activities. We then divide the sample based on the highest level of education completed: primary school or less, secondary school, and tertiary level degree and above. We define four labor market states from the observed data: Unemployed, Formally employed as employee, Informally employed as employee, Self-employed. We also consider the state of no labor market participation. Following Kanbur (2009) and Levy (2008), an employee is defined as informal when not contributing to the social security system. Finally, when considering women, we also report the presence of young children in the household. We consider two cutoffs based on schooling age: for pre-schoolers we use the cutoff at 5 years of age and for primary and lower-secondary we use the cutoff at 13 age of age.

A complete set of Tables with the descriptive statistics on the samples we use in estimation are presented in the Appendix E.[12] In Figure 1 we focus on one of the features we are most

[11]See Appendix B for a detailed description of the data sources and the sample construction

[12]Tables E.1, E.6, E.11, and E.16 report the number of observations in the sample (N); the average duration in unemployment expressed in months ($\bar{t}_u$); the average wage expressed in 2016 US Dollars ($\bar{w}$);

interested in: gender gaps. Figure 1 panel (a) shows that in all countries there is a strong gender asymmetry in participation rates. At least 90% of men participate in the labor market in all countries while female participation ranges from about 45% in Mexico to about 76% in Argentina. These gender differences generate gaps in participation rates in the range between 25 and 50%. Additionally, lower female participation rates mask important composition effects by education. In all countries, the higher the education level, the lower the gender gap in participation rate (between 14 and 30%). Also, the difference in participation rates between women with a completed tertiary education and women with only a completed primary education is dramatic in all countries (30 percentage points or more).

Figure 1 panel (b) shows that, conditional on participating in the labor market, the gender asymmetries are also significant in informality rates. In the figure, informal workers are comprised by informal waged earners and self-employed workers. In this case, men are more likely to be observed in an informal job, with informality rates that range between 26 and 55%. In the case of women this figure ranges between 15 and 40%. All in all, the gender differences in informality rates are as low as 30% in Colombia and as high as 50% in Mexico. Once again, composition effects by education are also masked in the compositions of jobs between the formal and informal sectors. In particular, the difference in informality rates between men and women with only a completed primary education are 40 and 50% in favor of women.

Figure 1 panel (c) shows that Argentina and Chile are the two extreme countries with respectively the highest and lowest gender gaps against women in weekly hours worked in all schooling groups. Also, the larger difference in weekly hours worked between men and women is observed in the group of only a completed primary education in all countries.

Figure 1 panels (d), (e) and (f) show gender differences in average wages by type of job. With the exception of Argentina, all countries exhibit the usual gender wage gaps against women. Chile is the country with the highest gender gaps against women in all types of jobs (more than 24% for formal employees and 21% for self-employed workers). Also, as is common in other middle-income countries and in high-income countries, the gender gap in average wages in Chile is increasing in education. In the cases of Colombia and Mexico this regularity is not observed. In particular, for informal employees and self-employed workers in these countries, the difference in the wage gap between those with primary education and those with tertiary education is as low as 10 percentage points.

Finally, the tables in the Appendix also highlight that the unemployment durations are

and the standard deviation of wages expressed in 2016 US Dollars (σ_w). We normalize the wage variables in dollars to ease the comparison between countries.

generally short, ranging from about to 2 to about 4 months on average. Gender differences in unemployment durations are typically not large.[13]

4 Estimation Method

The model is estimated by maximum likelihood on the data described in Section 3. For each country, education level and gender, we have information on labor market states, hourly wages, self-employment earnings and on-going unemployment durations. This information permits us to identify and estimate a very flexible specification: all the parameters of the model are allowed to vary by country, gender and education.

We build the likelihood contributions on observed wages, observed self-employed labor income, and observed on-going unemployment durations. In addition, we use information on the current labor market state of the agent. We use the labor market state information to build the contribution of non-participating in the labor market and to incorporate in the likelihood the fact that we observe labor income only for the currently employed and unemployment durations only for the currently unemployed. The complete derivation of the likelihood function is discussed and reported in Appendix C

From the likelihood contributions, it is possible to formally discuss the identification of the structural parameters of the model under some common distributional assumptions about the match specific productivity x and the out-of-labor-market utility z. The identification strategy closely follows Flinn and Heckman (1982) and Flabbi (2010b) and can be summarized as follows. First, the identification of the mobility parameters, hazard rates and the arrival rates of the termination shocks, is secured by the the unemployment duration information and the steady state equilibrium conditions. Second, the identification of the productivity distributions (in all types of jobs) requires a distributional assumption as shown by the non-identification result of Flinn and Heckman (1982). If the distributional assumption is recoverable, then the offer distribution can be recovered. Under the same distributional assumption, the hazard rate can be decomposed in the arrival rate components and in the probability of acceptance components. This step secure the identification of the mobility parameters. Third, the flow value of unemployment b and the discount rate ρ are only jointly identified since they enter the likelihood only through the reservation values.

[13]We do not report average durations on Argentina. The Argentinian data do not report individual unemployment durations as the other countries but only an interval to which the individual duration belongs to. Since we do not know where the duration actually is within the interval, we refrain from reporting the average. In estimation, we take into account this peculiar data feature by appropriately defining the likelihood function for Argentina.

Fourth, the identification of the out-of-labor-market utility distributions relies on the threshold crossing conditions implied by the model. The threshold crossing condition together with the proportion of individuals who participates allow for the identification of a one parameter distribution.

A complete and formal discussion of the identification is reported in Appendix D. Below we just list the specific distributional assumptions we make and the restrictions we have to impose on some parameters.

4.1 Distributional Assumptions

We follow the literature by assuming a log normal distribution for the match-specific distributions $G_{ij}(x)$ $(j = F, I, S)$.[14] We denote its location and scale parameters with μ_{ij} and σ_{ij}.

We assume a negative exponential for the out-of-labor-market utility distribution $Q_i(z)$. As mentioned, we are constrained to use a one parameter distribution in this case and the exponential is tractable and consistent with previous literature.[15] We denote its parameter with $\gamma_{i\kappa}$. The subscript $_{i\kappa}$ denotes that the parameter is not only a function of gender i but also of the presence of young children in the household. We add this feature to take into account that participation decisions are, in particular for women, strongly influenced by child-caring and child-rearing responsibilities. We consider three age groups: household with at least one child aged 5 or younger ($\kappa = k5$, pre-school); household with at least one child aged 5-13 ($\kappa = k13$, elementary school); and households where there are no children aged 13 or younger ($\kappa = other$).[16] While this parametrization allows to capture some impact of fertility, it is worth emphasizing that fertility decisions are still kept exogenous in our model. Most of the policy experiments we implement could potentially have an impact on fertility decision but this is one the equilibrium effects that we cannot capture in our setting.

As explained in Appendix D, we follow the common practice of adding measurement errors in wages and earnings. We assume a multiplicative measurement error ϵ so that

[14] The lognormal is a recoverable distribution and assures a good fit of the data. Previous works using the same distributional assumption include Flinn and Mullins (2015); Flabbi (2010b); Bobba et al. (2017) and most of the works cited in the survey by Eckstein and van den Berg (2007).

[15] Flabbi (2010b) make the same distributional assumption. Other contributions use the same assumption in similar threshold-crossing decision with unobserved heterogeneity, such as ex-ante schooling decisions, see Bobba et al. (2017); Flinn and Mullins (2015). Still, given its relative weak empirical identification, we provide a robustness analysis with respect to this distributional assumption: see comments to Figure G.1 in Appendix G.

[16] After preliminary analysis, we concluded that the estimates on men were not sensitive to the presence of children and therefore we introduce these differences only on the women's specifications.

observed wages can be expressed as $w^o = w \times \epsilon$. The assumptions we make about the measurement error are threefold: (1) they are gender- specific; (2) they follow a log-normal distribution with parameters μ_ϵ and σ_ϵ; and (3) they are such that the conditional expectation of the observed wages is equal to the true wages: $E[w^o|w] = w$, which implies that $E[\epsilon|w] = 1$. These assumptions imply that the parameters μ_ϵ and σ_ϵ satisfy $\sigma_\epsilon = \sqrt{-2\mu_\epsilon}$, and therefore only one parameter of the measurement error has to be estimated.

4.2 Parameters Restrictions

As mentioned, the flow value of unemployment b and the discount rate ρ are only jointly identified. Following again previous literature, we choose to fix the discount rate and to recover b through the equilibrium equation (A.5). We fix ρ in the range of 5.3 and 6.7% a year for the different countries and are borrowed from Lopez (2008).

The Nash bargaining parameter β is difficult to identify without demand side information.[17] Consistently with the common discount rate assumption, we assume symmetric bargaining and therefore we fix a β at 0.5. An additional limitation of this assumption in our context is that it does also imply that men and women share the same parameter. This could be a restrictive assumption because some previous contributions have suggested using the nash-bargaining weight as a proxy for possible discrimination (Eckstein and Wolpin, 1999; Bartolucci, 2013) and have suggested that women and men could be systematically different in their bargaining process (Castillo et al., 2013). While the evidence is mixed, in Figure G.2 in Appendix G we provide a robustness analysis where we allow the coefficients to be different between men and women. Except for one schooling level in Colombia, we do not find the relevant results to be sensitive to this restriction.

Another parameter hard to identify without additional information is the cost of informality c. We choose to use information from one of the few paper estimating search models of the labor market with informality, Bobba et al. (2017), to fix the parameter at a reasonable order of magnitude. Specifically, we set it as the ratio between the cost of informality and the average wage in the formal sector estimated by Bobba et al. (2017).

The pay-roll tax rate τ is an Institutional parameter that we observe and it does not need to be estimated. We use information on payroll contributions in each country to set it at values ranging from 0.48 in Argentina to 0.20 in Chile.

As shown in Equations (D.1)–(D.6) in Appendix D, a system of six nonlinear equations in

[17] For a formal discussion, see Flinn (2006). For an implementation using demand-side information, see Cahuc et al. (2006).

six unknowns identify (h_j, δ_j). However, as a result of issues with empirical identification,[18] we have chosen to follow Bobba et al. (2017) and restrict the set of possible solutions to those that satisfy $\lambda_F = \lambda_I$ and $\delta_F = \delta_I$. The constraints implies that employee jobs share the same arrival and termination rate.[19]

5 Estimation Results

The complete parameter estimates are reported in Appendix E. The estimates are quite precise, typically more so the higher the education level and the larger the sample size. The estimates also report significant differences for many parameters by gender, country and education. Four comments about those differences are worth mentioning.

First, as shown in Figure 2 Colombia has the lowest arrival rates in the formal/informal sector and the differences with respect to the other countries are statistically significant. Additionally, in all countries, the biggest (and statistically significant) differences between arrival rates in the formal/informal sector of men and women are in the group of workers with primary education. Second, in all countries, the termination rate of formal/informal jobs is lower in the group of workers with tertiary education. The differences with other educational groups are evident and statistically significant for Argentina and Chile. With respect to gender, termination rates of formal/informal jobs are in general higher for women. Third, as shown in Figure 3, productivity is typically lower for women in formal jobs while it is frequently equal or higher in informal jobs and self employment. The differences are not always statistically significant but they are definitely so for Primary in Argentina and Mexico and for Tertiary in Colombia and Chile. The clearest gender gaps in productivity is in Primary in Mexico where all the three productivity distributions generate significantly lower means women. Additional comments on productivity are reported below. Fourth, as shown in Figure 4, the value of participating in the labor market (ρU) shows a significant gender gaps for men and women in the Secondary and Tertiary education group. Argentina is the only one exhibiting modest returns to schooling to Tertiary since Tertiary and Secondary values are quite similar.

[18] For a significant number of estimation samples we do not have enough data variation to obtain convergence of the likelihood function in the feasible parameters space.

[19] In Appendix G Table G.1, we perform a robustness analysis on the only country on which it is possible to attain empirical identification on all estimation samples: Argentina. For Argentina, we estimate the model both imposing equality of the parameter and allowing the parameters to be different. We then perform a Likelihood Ratio test where the null is the restricted model and the alternative is the unrestricted model. The restriction is rejected only on one sample out of six: men with Secondary education. Even in this case, the differences in point estimates are not large.

Among the structural parameters, the parameter $\gamma_{i\kappa}$ is of particular interest since it is the parameter governing the distribution of the utility when non-participating in the labor market. As expected, the presence of young children in the household increases the value of out-of-labor-market activities. The difference may be substantial. For example, in Colombia among tertiary educated women, the average value of out-of-labor-market activities when a children younger than 5 is present is almost 30% higher than when no children younger than 13 are present.

Tables E.4, E.9, E.14, and E.19 report the implications of the parameters estimates on productivity and wages. The top panel of each table reports expected value ($E[x]$) and standard deviation ($SD[x]$) of the match-specific productivity in formal employment, informal employment and self-employment. They describe the primitive productivity distributions that we denoted with $G_{ij}(x)$ in the formal modal and they represent the potential output of a given match between a worker and a firm. Some of these matches are realized (accepted) and some are not, depending on the optimal decision rules of the agents (see Section 2.4). The bottom panel of each table reports expected value and standard deviation of the accepted wages in formal employment and informal employment and of the realized labor income in self-employment. Notice that the relation between the top panel and the bottom panel involves two steps. The first step is the mapping between a specific value of productivity x and the wage paid to the worker w. This relation is governed by the equilibrium equations (9) and (10). The second step is the optimal decision rule: not all the matches are acceptable. Only matches with productivity higher than the appropriate reservation values – as defined in equations (A.2) and (A.3) – are realized in equilibrium. In the case of the self-employed, the mapping between productivity and realized labor income only involves the second step. Finally, the middle panel of each Table reports the implied output per worker (Y^{pw}) and output per capita (Y^{pc}) defined in equation (A.14)–(A.14). It is a useful measure to evaluate the policy experiments and it represents the total value of the production of a given group in the economy. It does take into account that: (i) agents may spend time in different labor market states, including unemployment; (ii) agents may be less or more productive if they work formally or informally; and, (iii) some agents may not participate in the labor market at all.

The first relevant result reported in the top panel was expected: productivity increases with education in all countries and for both men and women. The second result is less obvious: the average gender gap in productivity is sometimes very different from the average gender gap in wages. If the gender gap in wages typically favor men, that is not always true of the gap in productivity. For example, in Colombia, the average productivity of women with secondary education working as formal employee is about 11% higher than the average productivity of the corresponding group of men but their accepted wages are about 10% lower. Even if women may have on average higher productivity, they may decide to accept lower wages as a result of different arrival rates of offers, different values of the outside option while bargaining and different values of out-of-labor-market activities.

5.1 Fit

The bottom panel of Tables E.4, E.9, E.14, and E.19 is also useful to judge how well the estimated model fit the data. Each table reports the simulated moments (denoted by *Model*) side-by-side with the sample moments (denoted by *Data*). The fit of the model is quite good on the means but in some instances it is unable to fit the standard deviations.

Goodness of fit on the other labor market variables – including participation rates and labor market dynamics over the other labor markets states – are reported in Tables E.3, E.8, E.13, and E.18. The fit is great in Colombia, Chile and Mexico while it is markedly worse in Argentina. The worse result on Argentina is due to the less precise information available in the data: as mentioned, the duration information is not reported continuously but in intervals.

6 Policy Experiments

In this Section we use the estimated model to implement a wide range of policy experiments and to study their impact on relevant labor market outcomes. In each experiment, we change the value of the parameter of interest leaving the other parameters unchanged so as to isolate the impact of the policy under consideration. We simulate outcomes in the post-policy environment taking into account that agents' optimal decisions may change. In other words, we compute new reservation value rules at the new equilibrium generated by the policy. The equilibrium effects we can capture are limited to the ones explicitly modeled, as described in Section 2. In particular, since we estimate the model under the assumption that market are segmented by country, education level and gender, there cannot be spillover effects between these groups.

6.1 Definition

In the first two experiments, we study both the reasons behind and the losses implied by the lower labor market participation of women with respect to men. Women may decide to participate less then men either because the value of non-participation is higher or because the benefit of participating in the market is lower. The first experiment relates to the first component: the value of non-participation. The second experiment relates to the second component: gender asymmetries in labor market opportunities. The third experiment implements a policy suggested by the gender-based taxation literature.

Both opinion surveys and economic literature indicate that women value more than men time outside the labor market.[20] Our own estimates show this to be the case since the average value of non-participation $E(z)$ is estimated to be higher for women than men in all education groups. Many factors may impact this difference, such as preferences, household production, abilities and attitudes. One major component seems to be child-care and child-rearing. Women still invest a higher amount of hours in child-care than men and their labor market participation is significantly affected by fertility outcomes (Burda et al., 2013). Many policy tools may have an impact on this value. For example, good and affordable childcare provisions may decrease the benefit of mother's time in child-rearing and induce them to work more. Numerous policies are focusing on providing good and affordable childcare, using either a voucher system that provides subsidies to parents that use childcare or a direct public provision of the service.[21] To map this policy in our model we change the parameters governing the flow utility of non-participation z. Specifically, we allow the distribution of values of non-participation to be different between women with children 5 or younger, children between the age of 5 and 13, and without children younger than 13. Since child-care provision policies are more likely to affect mothers with young children, *Policy Experiment 1* reduces the average value of non-participation for those mothers in half. Formally, it is equivalent to doubling the parameter γ_{k5}. Reducing the value in half is arbitrary but, as we will show when discussing the results, seems to generate labor supply responses in line with some estimates available in the literature. To gain more flexibility in this respect and to study possible non-linearity of the policy impacts, we also present selected results on the the same policy where we vary the average value of non-participation for mothers with children

[20]For example, Scandura and Lankau (1997) show that women value more than men flexible working arrangements in order to perform activities not related with the labor market.

[21]Examples of specific policies in the region include: construction of pre-primary school facilities in Argentina (Berlinski and Galiani, 2007); subsidized provision of after-school care in Chile (Martínez and Perticará, 2017); a large subsidized childcare program in Colombia (Bernal and Fernández, 2013).

5 or younger over a broader range: from a 25% to a 75% decrease.

Gender asymmetries in labor market opportunities are the results of many components, including the gender wage gap, differences in promotions and labor market careers, asymmetries in search intensity and occupational choices. Some of these differences may be due to differences in preferences and attitudes but other may relate to issues affected by policies such as human capital accumulation, gender discrimination, occupational choices. For example, a policy that gives incentives to women to enroll in STEM or an affirmative action policy aiming at reducing discrimination can both be seen as policies boosting women productivities.[22] In this spirit, *Policy Experiment 2* increases the average productivity of women in the three sectors by 10%. Since productivity is represented in our model by the distributions $G_{i,j}(x)$, formally, the experiments changes the parameters μ_{Wj} and σ_{Wj} for $j = F, I, S$ so that the new average productivity $E_{Wj}(x)$ is 10% higher. We chose 10% to ease the calculation of the elasticities but it is worth noticing that in many cases a 10% increase is enough to close the gender gap in productivity. This is true in most countries among workers with secondary and tertiary education completed.[23] Among workers with only primary education completed, instead, the gaps are typically larger, ranging from 20% to 30% and therefore a 10% increase is not enough to generate the same average productivity between men and women. As in the previous experiment, 10% is a useful reference point but it is arbitrary. To study the impact on a broader range of values, we also implement experiments changing average productivity over a grid of values ranging from 1% to 20%.

In the third experiment, we study a policy inspired by the gender-based taxation literature (Alesina et al., 2011; Meier and Rainer, 2015). This literature suggests that the systematic differences in labor supply elasticities between men and women should be recognized by the tax system in order to improve efficiency. Since the labor supply of women is more elastic, efficiency considerations imply that women's labor should be taxed at a lower rate than men's labor. We implement this policy by imposing a gender-based contribution rate for formal employees. In the notation of the paper, we change the parameter τ denoting the proportional rate at which payroll social security contributions are withdrawn at the source by firms when the job is formal. *Policy Experiment 3* imposes a contribution rate 30% lower for women than men. The contribution rates for men remain at the baseline value for each country.

[22]For an example of the first in LAC, see Bustelo et al. (2017).

[23]A notable exception is Chile, which is registering the largest gender gap in productivity in the tertiary education group: we estimate the average productivity of women about 20% lower than the average productivity of men. See the last column of Table E.9.

In the fourth and last experiment, we implement two extreme policies to compare formality and informality costs. These costs are the payroll contribution rate τ paid on formal matches and the flow and fixed cost c paid on informal matches. The parameters of the two formality regime are not only different but also have different ex-post distributive effects. Lower productivity matches are penalized relatively more than higher productivity matches by the fixed cost of informality c. Since lower wages are associate with lower productivity matches, this cost is regressive while the cost of the formal contribution rate is proportional. It does therefore become interesting to assess which one of the two has the bigger impact gender differences in the labor market. *Policy Experiment 4* performs two simple counterfactual exercises: first sets the contribution rate τ to zero and study the effects on the new equilibrium. Then it repeats the same procedure setting the cost of informality c to zero.

6.2 Results

6.2.1 Policy Experiment 1: Reducing mother's value of non-participation

Panels (a) and (b) of Figure 5 report the impact of the policy experiments on two crucial variables of interest: participation rates and output per capita. The impact on a larger set of variables and labor market indicators is presented in a series of Tables in Appendix E. The impact of the childcare provision policy on female participation rates (panel a) is positive across the board with changes ranging between 7 and 8 percentage points. However, in most cases the intervention is not enough to close the gender gap in participation.

There is a large literature looking at the impact of child care policies on female labor supply. The empirical contributions typically exploit institutional reforms to estimate impacts based on difference-in-difference approaches. As a result, the change in the policy variables cannot be directly mapped in the change in our policy parameter but the magnitude of the change in female labor force participation can be. Blau and Currie (2006) present a review of child-care programs' arrangements and impacts. The policies more similar to our exercise are those providing subsidies to buy childcare services. They review various studies in the U.S. and they report increases in maternal employment ranging from 5 to more than 30 percentage points. It is a quite broad range but it is a range that includes all the values that we find in our experiments: from the 5.3 percentage points in the tertiary group that we find in Colombia to the almost 10 percentage points in the primary group that we obtain in Argentina. Baker et al. (2008) estimate the impact of a highly subsidized, universally accessible child care provision program in Quebec. They find an increase in labor force participation of

7.7 percentage points, a value very comparable to those implied by our experiments in the secondary education group in most countries in our sample. As a reference, the participation rate in the Quebec's estimation sample was about 53% at baseline. Felfe et al. (2016) use variation in cantonal regulations of after-school care provision in Switzerland but they find no impact on overall employment rate. They however find some positive and significant impact on the intensive margin of labor supply. One possible difference from our results is that overall female participation in Switzerland is higher than in our sample so that the main margin of adjustment becomes the intensive margin of labor supply.

There are also studies that look at some of the countries included in our estimation sample. Berlinski and Galiani (2007) evaluate the impact of a large construction of pre-primary school facilities in Argentina and find effects of magnitude similar to our exercise: an increase of 7 percentage points in maternal employment. Maternal employment is different from participation due to the possibility of unemployment but since unemployment is quite low in our estimation sample, the number remains comparable: the aggregate impact of our policy for Argentina is an increase of 8 percentage points. Martínez and Perticará (2017) provides an identification strategy based on a randomized experiment offering after-school care and they find an increase in maternal labor force participation of 4.3 percentage points. Our experiment on Chile reports higher increases, ranging from 6.8 to 8.9 percentage points. However, we focus on children at a younger age than those in the Martínez and Perticará (2017)'s study.

The increase in the participation of women in the labor market translates in an increase in output because more workers contributes to production in the market. The increases in output per capita (panel b) are substantial. For example the output per capita in Mexico will permanently increase by more than 6% as a result of the policy. The other countries register an impact that is smaller but never less than 4% resulting in an overall average of 5.5%. In addition to differences by countries, there are differences by education groups. In Argentina, the policy has a higher impact for lower education groups; in the other countries the highest impact is on the secondary education group. It is important to notice that we report *total* increases in output and not yearly increases or increases in growth rate. How long it would take for the increase in output to take place depends on how long it would take for the policy to be implemented.

It is also important to recall that we have modeled our economy on a "per-hour" basis, i.e. we are using hourly wages to estimate the model and therefore the match-specific productivity x that we use to compute output should also be interpreted on an hourly basis. However, there is ample evidence showing that gender differences in labor supply are not only limited to the extensive margin (the participation decision) but include also the intensive margin (hours worked). We illustrate the sensitivity of our results with respect to this gender differential with the darker and lighter colors reported in panel (b) of Figure 5. The total height of each bar is the "per hour" increase. Alternatively, it could be seen as the increase that would result if men and women where working the same average number of hours when they participate in the labor market. The lighter part of the histogram's columns takes into account that men and women can in fact work different hours on average when they participate in the labor market. Specifically, we compute them assigning to men and women the average amount of weekly hours observed in the data. As expected, the increases in output are all lower because, on average, women work less hours than men in all the countries over all education levels. How much lower is denoted by the larger part of the bar. However, the difference does not eliminate the large positive impact on output and for many country is quite small. The highest reduction is in Argentina and Mexico but it is still limited to less than one percentage point in both countries.

In the experiment discussed so far, we reduced the average value of non-participation for mothers with children aged 5 or younger in half. To match other possible policy experiments and to study possible nonlinearities in the optimal reactions to such policy changes, we also performed the same experiment by changing the average value of non-participation over a broader range. Results are reported in Figures F.1 and F.2 in Appendix F. Both graphs show monotone effects and a quite linear impacts when we reduce the value on a grid from 25% to 75%. An important exception is Mexico, showing a higher sensitivity for higher values of the reduction: a reduction of 75% in the value of non-participation would increase female participation by 16 percentage points and output by 12; a reduction of 25% would increase participation by less than 4 percentage points and output by less than 3.

6.2.2 Policy Experiment 2: increasing women average productivity

Panels (c) and (d) of Figure 5 report the impact of the experiment increasing women productivity by 10%. The impact on participation rates (panel c) is large across the board and it is massive on groups with only primary education. On these groups, the participation rate increases by more than 20 percentage points leading to almost full participation in the case of Argentina. As expected, the impact on output per capita is very large among these groups, as reported in panel (d). However, the impact on overall output per capita, while still large, is not as massive since the primary education group is the least productive education group in each country. It is very interesting to see how the aggregated increase in output per capita is always larger than the increase in women productivity we have imposed with our policy (10%). The additional effect is due to changes in reservation wages and to the higher female participation in the labor market. This channel is made more explicit by the decomposition reported in Figure F.3 in Appendix F. The overall increase is decomposed in the portion directly due to the 10% productivity increase (Pure Productivity Effect) and the portion due to the increase in participation resulting from the productivity increase (Labor Force Effect). The second effect is the optimal reaction of the agents to the new environment, what we called equilibrium effect. In other words, it is the impact on output implied by the increase participation that we have seen in panel (c) of Figure 5. Figure F.3 shows that the equilibrium impact to the change in participation is not only significant but actually larger than the direct increase in productivity. This explain the magnifying effect noted above: a 10% increases in productivity increase output by significantly more than 10%.

As in *Policy Experiment 1*, we illustrate the sensitivity of our results with respect to gender differentials in the intensive margin of labor supply with the darker and lighter colors reported in panel (d) of Figure 5. The lighter part of the histogram's columns takes into account that men and women work different hours on average when they participate in the labor market. As before, there is a reduction of the positive impact when we take this into account but the reduction is even smaller than in the previous case, in particular for groups with more education.

The results of experiments changing the range of the productivity increase are reported in Figures F.4 and F.5 in Appendix F. We perform experiments on a grid of values ranging from 1% to 20%. The impacts on participation are more non-linear than in the previous experiments: the elasticity decreases as we increase the average productivity. This is not the case on the output impact. The reason is that, as pointed out before, the overall increase in output is due to two channels: the increase in productivity in the women population (Pure Productivity Effect) and the portion due to the increase in participation resulting from the productivity increase (Labor Force Effect). The lower increase of the second effect is compensated by the larger increase of the first, generating an overall impact which is approximately linear.

Finally, we perform an experiment where we decompose the impact of the productivity increase by sector. In Figure F.6 in Appendix F, we report the impact on participation and output of increasing women productivity by 10% in one sector at the time: the formal employee sector, the informal employee sector and the self-employed sector. On top of providing a useful decomposition, these experiments may correspond to actually different policies. For example, a small business training program may increase women's productivity in the self-employed sector but not so much in the other two. We find that increasing productivity only in the formal sector generates smaller but comparable overall effects on participation as the baseline experiment. The main difference is that tertiary educated women are now the largest beneficiaries. Increasing productivity only for informal employee has positive but much smaller impacts than at baseline, in particular on output per capita. The increase in self-employment productivity generates a larger impact on output per capita than the increase in informal productivity but smaller than the one in formal productivity.

6.2.3 Policy Experiment 3: decreasing women contribution rate

Panels (e) and (f) of Figure 5 reports the impact of imposing a gender-based contribution rate for formal employees. As in the previous figures, the top panel shows the impact on the female participation rate and the bottom panel the impact on the output per capita.

The impact on the participation rate (panel e) is present but limited. A more important impact is present in the composition of the participation. Since the policy reduces the cost of formality, a larger proportion of labor market participants work in formal employee jobs, in particular at higher levels of education. Results are in Tables E.5, E.10, E.15, and E.20 in Appendix E.

The impact on output (panel f) is large but the result may be more an indication that the tax is distortionary in general than a suggestion of a gender-specific advantage. The main reason reason why taxes may have a relatively limited impact on participation is that they are shared between the worker and the firm. The bargaining structure, see 2.3, delivers this result, a result that effectively dampens the elasticity of workers' labor supply with respect to the contribution rate. Another reason why the impact on the overall female participation rate is limited is that workers and firms substitute informal employment for formal employment. As a result of the policy, the overall participation rate does not change too much but its composition does, moving women from informal to formal employment options.

6.2.4 Policy Experiment 4: formality costs vs informality costs

Figure 6 reports the impact of two policy experiments. On the left, we eliminate the cost of formality by setting $\tau = 0$; on the right, we eliminate the cost of informality by setting $c = 0$. Both policies increase overall female labor force participation (top panel) but the distribution of the increase is very different. Removing costs of formality increase more the participation of highly educated women; removing costs of informality has exactly the opposite effects. The reason was mentioned in Section 6.1: the informality cost penalizes proportionally more low-wage matches, which are in turn over-represented among women with lower education. At the same time, the formality costs is proportional to wages but since highly educated women are more likely to work formally, it does have a larger effect on them. This dynamic is reflected in the distribution over the four different labor market states: formal employee, informal employee, self-employed and unemployed. As shown in Tables E.5, E.10, E.15, and E.20 in Appendix E, the first policy increase the proportion of female workers in formal employee jobs while the second in informal employee jobs. The impact is larger for higher levels of education in the first case and for lower levels of education in the second case.

The composition effects over education are even stronger on output per capita, as shown in the bottom panels. Both have a positive impact overall but while removing payroll contributions has a positive impact on all the education levels, removing the informality costs has a positive impact only on the lowest education level.

To summarize, removing payroll contributions has the larger positive impact on both outcome variables for the secondary and tertiary education level while the most beneficial policy for the primary education level is removing the informality cost.

At the end of the policy experiments section, we should mention a relevant limitation useful to put the magnitudes we find in context. The demand side of the economy (the firms side) is very stylized and has very limited margins for adjustment. When a policy is implemented in the current model's environment, the "equilibrium effects" consists in the adjustment of the optimal decision rules for both firms and workers. However, the only margin of adjustment are the reservations values that generates the equilibrium proportions in the different labor market states. Workers can therefore decide over a variety of options but firms can only decide if accepting or rejecting workers and if hiring workers formally or informally. This means that firms cannot adjust their vacancy-posting strategy. If they were allowed to do that, the post-policy contact rates could potentially change while in our post-policy environment we keep them fixed at the estimated values. This additional equilibrium channel could both increase or decrease the impact of a policy change, depending on parameters and on the policy under consideration. Theoretically, it would be feasible to add this margin to the model. The issue is empirical: we do not have enough demand side data to identify the parameters of the matching function and the flow value of posting a vacancy.[24] Our experiments should then be interpreted as a reliable estimate of the impact

[24]The lack of data is exacerbated by having different schooling levels: at the minimum, we would need

of policy changes *before* firms can fully adjust their vacancy-posting behavior.

7 Conclusion

Gender gaps in the labor market are widespread in most world regions and Latin America (LAC) is no exception. However, LAC labor markets share some crucial features that may impact the gender gap and related policies. The most prominent feature is the presence of a large informal sector, which include both employee hired illegally and self employed workers operating outside the formal taxation and social protection system.

In the paper, we develop a search model of the labor market that captures both the essential features of LAC economies and the crucial aspects of the different behavior and opportunities of men and women in the labor market. The model includes job offers from formal and informal employment as well as self-employment opportunities. It also allows for a participation decision based on utility values affected by the presence of young children, in addition to gender-specific parameters describing labor market mobility and productivity.

We estimate the model on comparable data extracted from four large LAC countries: Argentina, Chile, Colombia and Mexico. The estimation results confirm some expected regularities (positive returns to schooling, a significant gender gap in wage and participation) but also imply some new conclusions. Prominent among the latter is the comparison between the gender gap in productivity and the gender gap in wages. For some countries and educations levels, the usual gender gap (men higher than women) is confirmed on wages but is reversed on productivity.

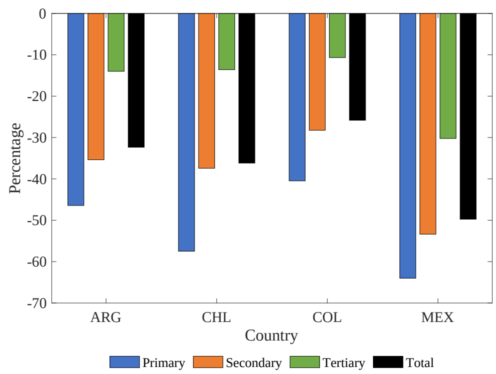
We exploit the estimated structural parameters of the model to perform four policy experiments. The first approximates a child care policy and the second polices able to increase average female productivity. The third imposes a gender-based contribution rate and the fourth studies the differential impacts of eliminating the costs of formality and informality.

We find that participation decisions significantly magnify the impact of each policy. For example, the policy increasing women productivity by 10% leads to a much larger increase in output per capita, ranging from 15% to 22%. This larger increase is due to the larger participation of women in the labor market which endogenously results from the policy. Composition effects over education are also important: most of the magnifying effects is

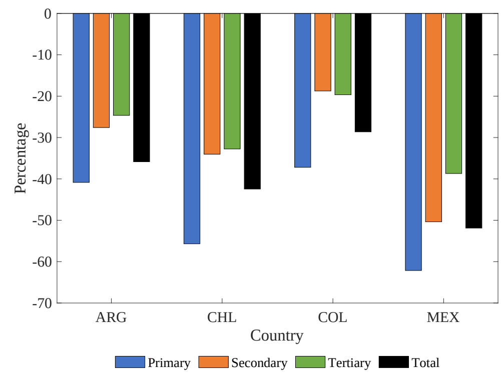
vacancy rates *by schooling* to identify the model and this would still impose a constrain on the TFP parameter of the matching function, essentially setting it to 1. We do not see a way to solve this identification problem over all schooling levels and countries object of our study.

driven by the group of women with the lowest education (primary schooling). In the fourth experiment, we find that removing payroll contributions has the larger positive impact on both outcome variables for the secondary and tertiary education level while the most beneficial policy for the primary education level is removing the informality cost. Finally, the policy approximating child care provision also significantly increases output per capita, ranging from an increase of 4.5% for Colombia to 6.6% for Mexico. This is a large increase for a policy that could be potentially implemented at a modest fiscal cost.

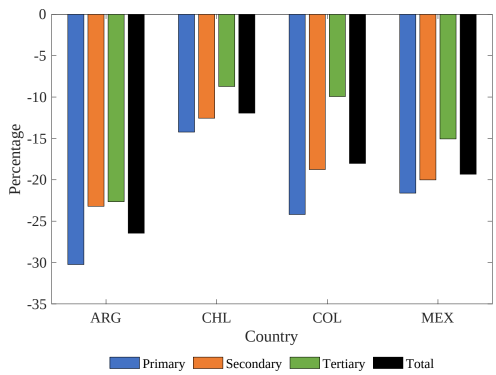
Figure 1: Gender Gaps in the Labor Market



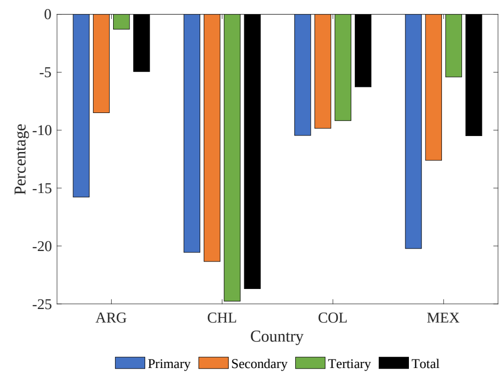
(a) Participation Rates



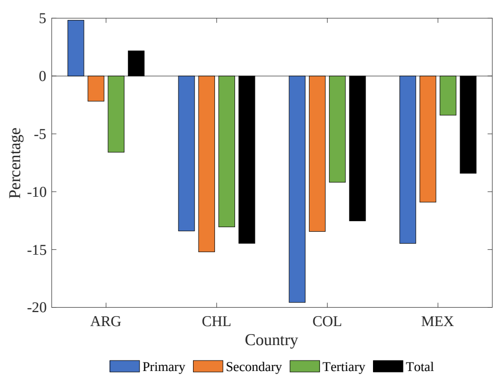
(b) Informality Rates



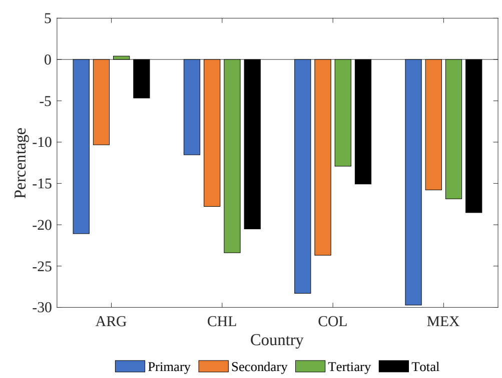
(c) Hours Worked



(d) Hourly Wage Formal Workers



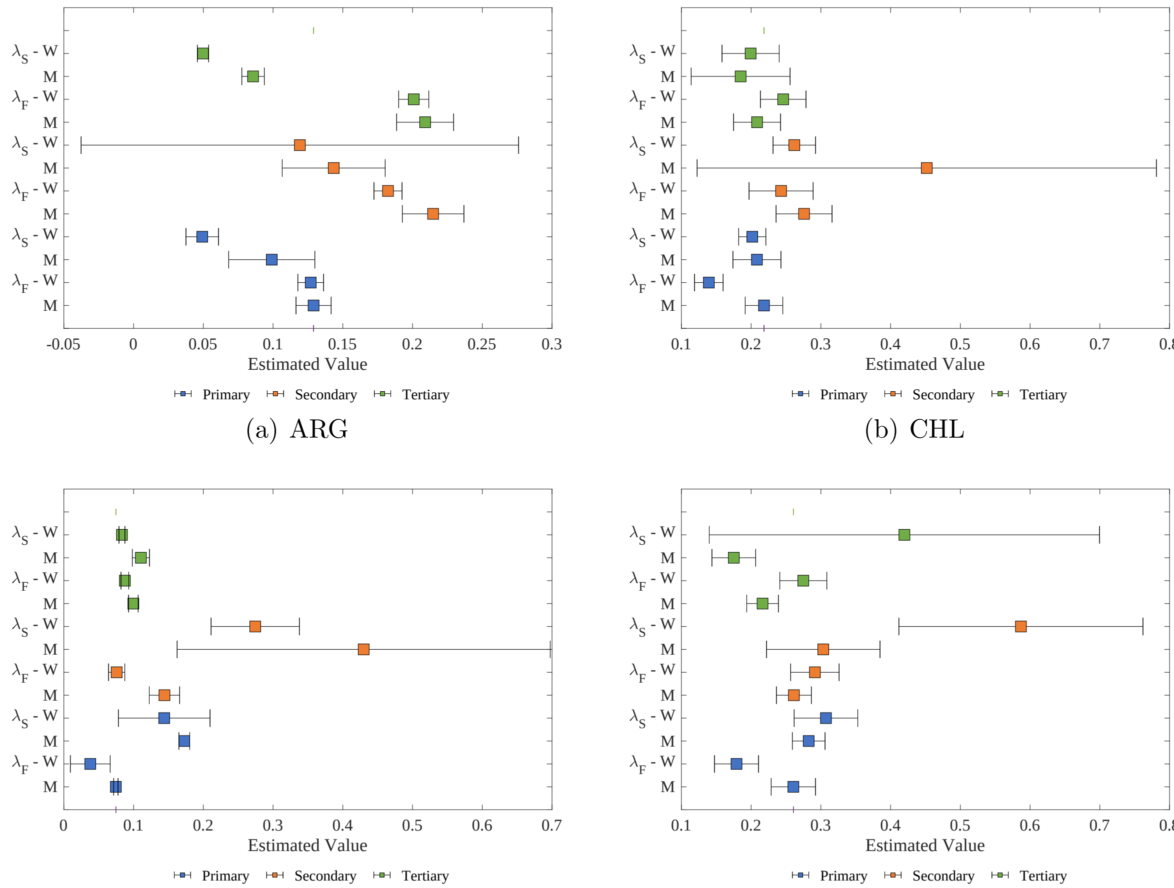
(e) Hourly Wages Informal Workers



(f) Hourly Wages Self-employed

NOTE: Values are computed on the estimation samples for each country. See Section 3 for data sources. Results report the ratio $\frac{X_W - X_M}{X_M}$, where X means the participation rate, the informality rate (including both informal wages workers and self-employed), the weekly hours worked, and the hourly wages. W and M denotes women and men, respectively.

Figure 2: Estimated Arrival Rate of Jobs

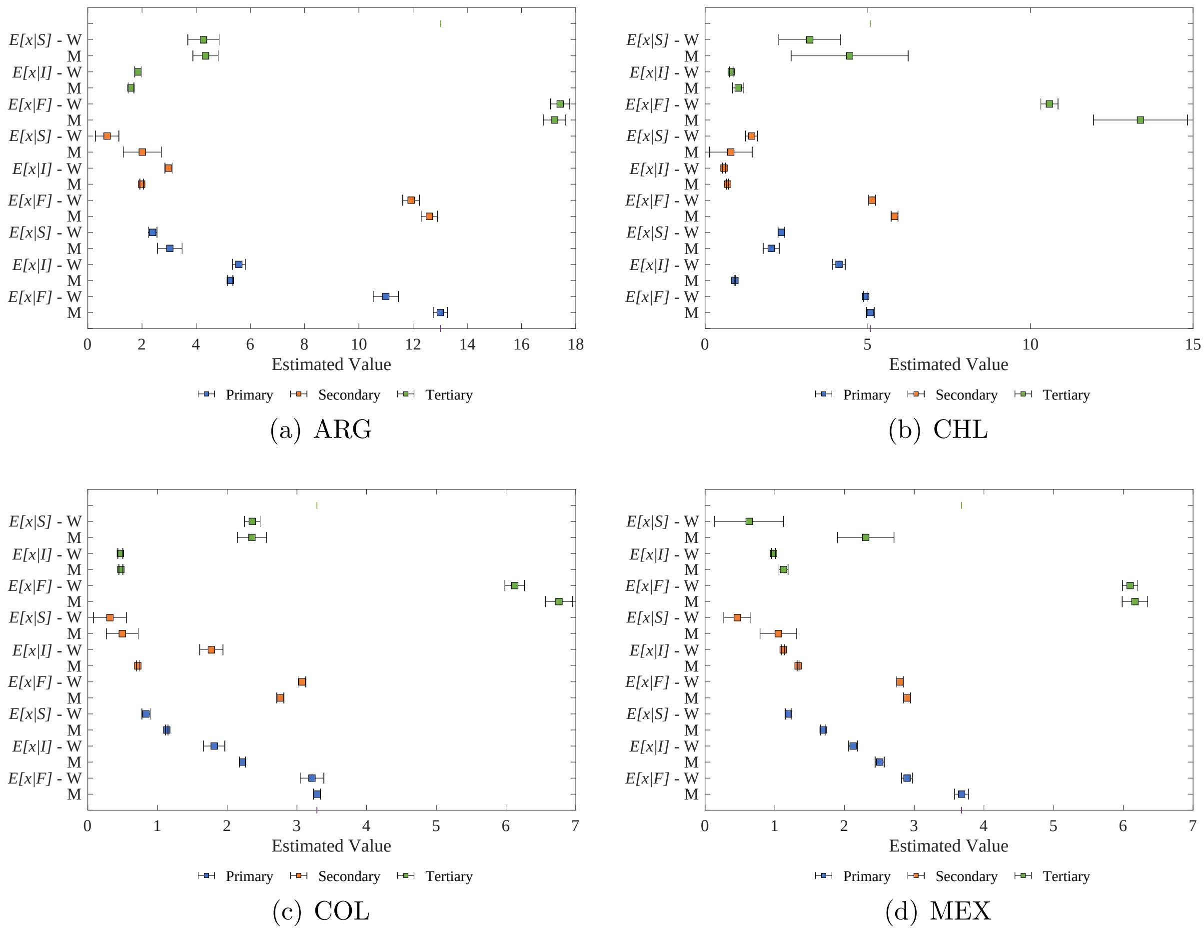


(a) ARG (b) CHL

(c) COL (d) MEX

NOTE: Based on the estimated results presented in Tables E.2, E.7, E.12, and E.17. The confidence bands reports the 95% confidence intervals based on bootstrapped standard errors with 100 replications.

Figure 3: Estimated Average Productivity



(a) ARG

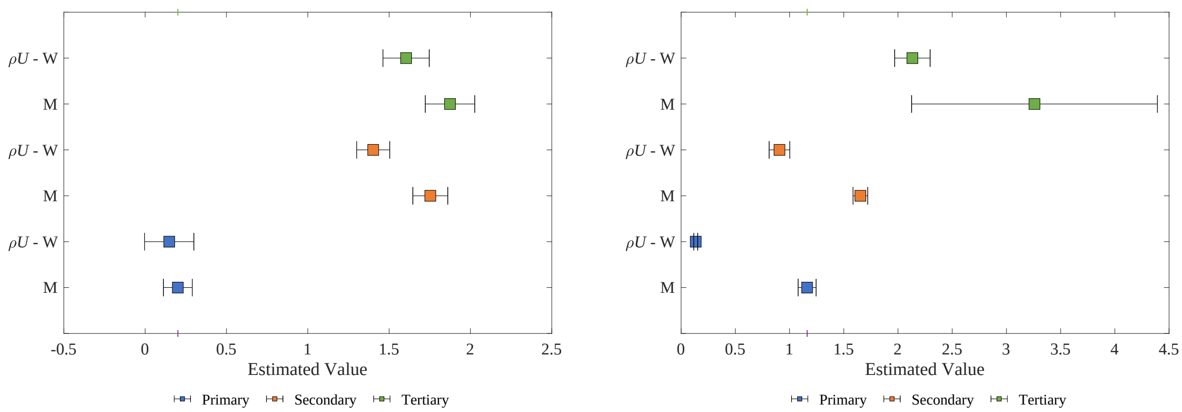
(b) CHL

(c) COL

(d) MEX

NOTE: Based on the estimated results presented in Tables E.2, E.7, E.12, and E.17. The confidence bands reports the 95% confidence intervals based on bootstrapped standard errors with 100 replications.

Figure 4: Estimated Discounted Value of Participating in the Labor Market



(a) ARG

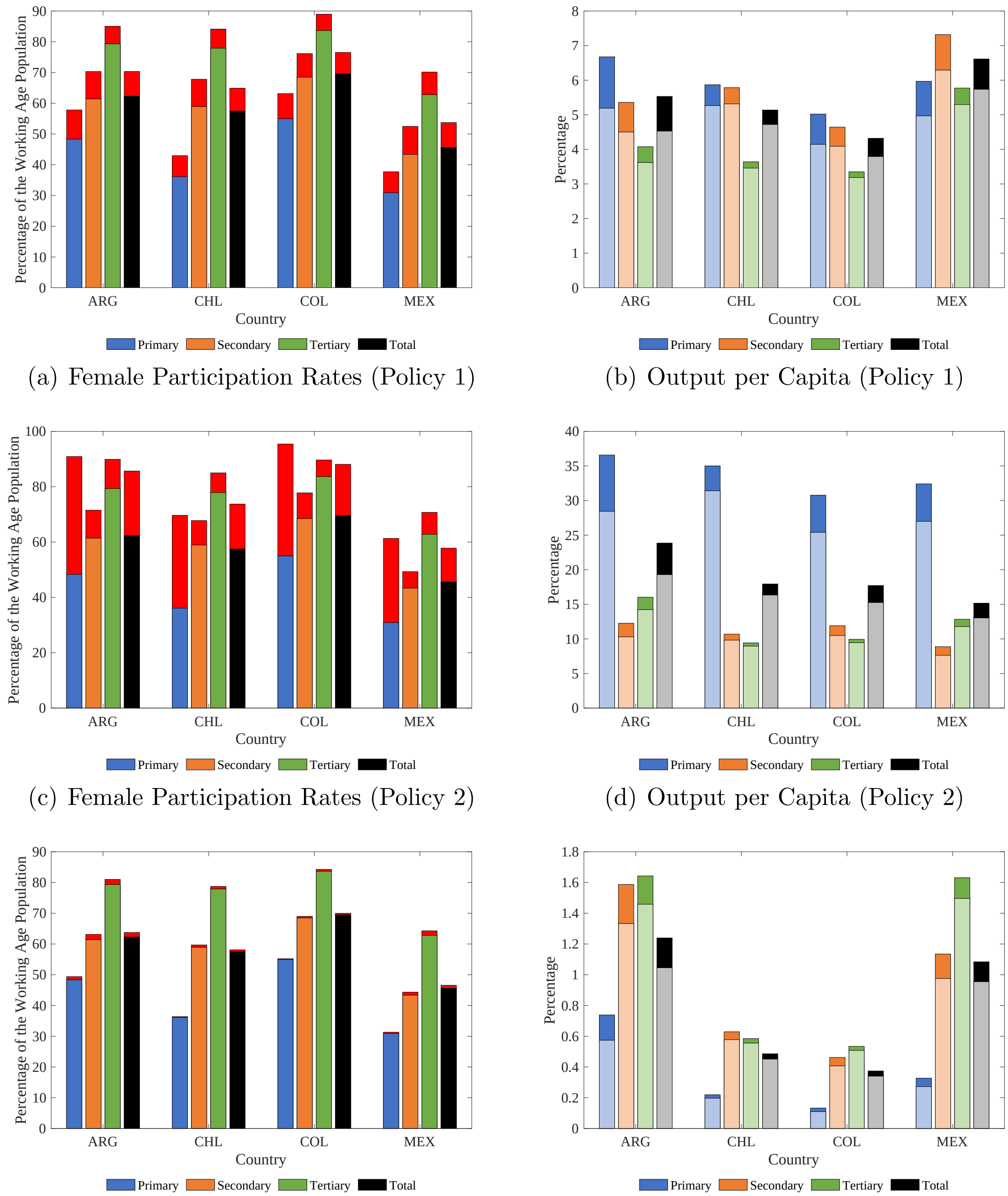
(b) CHL

(c) COL

(d) MEX

NOTE: Based on the estimated results presented in Tables E.2, E.7, E.12, and E.17. The confidence bands reports the 95% confidence intervals based on bootstrapped standard errors with 100 replications.

Figure 5: Policy Experiments: Reducing Mother's Value of Non-participation, Increasing Women Productivity and Decreasing Women Contribution Rate



(a) Female Participation Rates (Policy 1)

(b) Output per Capita (Policy 1)

(c) Female Participation Rates (Policy 2)

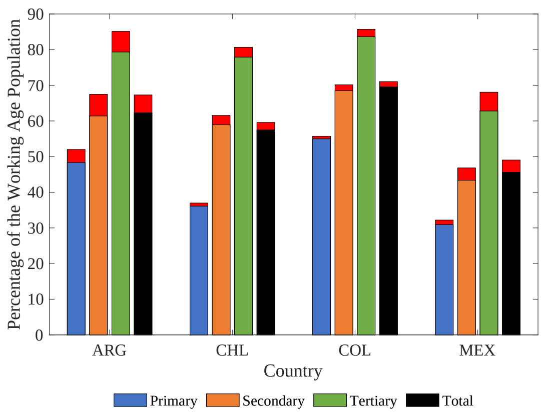
(d) Output per Capita (Policy 2)

(e) Female Participation Rates (Policy 3)

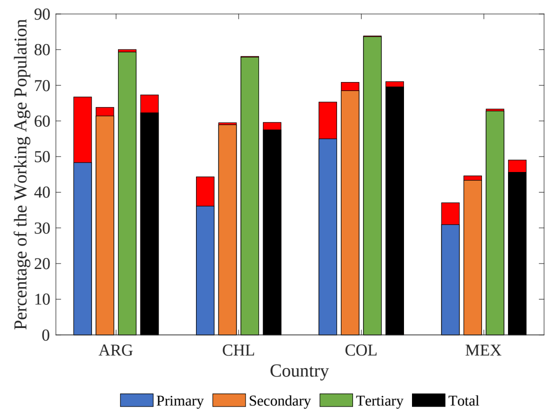
(f) Output per Capita (Policy 3)

NOTE: *Policy 1*: reducing in half the average value of non-participation for mother with children aged 5 or younger. *Policy 2*: increasing the average productivity of women by 10%, keeping the variance of the productivity constant. *Policy 3*: the formal employees contribution rate for women is set 30% lower than the one for men. In panels (a), (c) and (d) the overall length of the column is the post-policy participation rate. The red darker segment is the impact of the policy. In panel (b), (d) and (f) we report the percentage points changes in output as a result of the policy. Light colored bars represent the effect on output taking into account differences in average weekly hours worked by men and women. See Section 6 for more details.

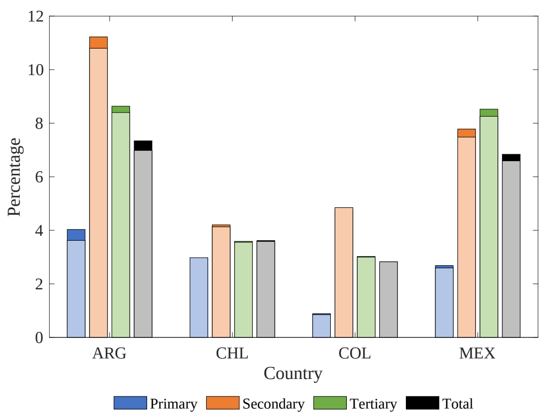
Figure 6: Policy Experiments: Comparing No Formality Costs and No Informality Costs



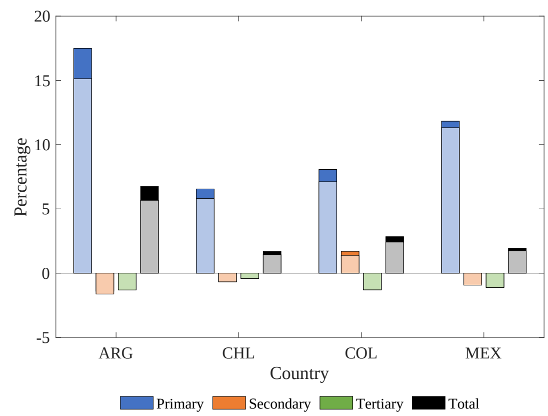
(a) Impact on Female Participation Rates ($\tau = 0$)



(b) Impact on Female Participation Rates ($c = 0$)



(c) Impact on Output per Capita ($\tau = 0$)



(d) Impact on Output per Capita ($c = 0$)

NOTE: *Policy 4*: panels (a) and (c) set the formal payroll contribution rate τ to zero; panels (b) and (d) set the cost of informality c to zero. In panels (a) and (b) the overall length of the column is the post-policy participation rate. The red darker segment is the impact of the policy. In panels (c) and (d) we report the percentage points changes in output as a result of the policy. Light colored bars represent the effect on output taking into account differences in average weekly hours worked by men and women. See Section 6 for more details.

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Appendix

A Model

The equilibrium of the model has a simple structure. Agents have to make two discrete choices. The first concerns labor market participation: either they participate in the labor market looking for a job (state U_i) or they stay out enjoying utility from out-of-labor-market activities (state NP_i). Since agents receive different utility from these activities (z), those receiving relative high utility will stay out, those receiving relative low utility will enter the market. The threshold for staying out or coming in is determined by the indifference point between the two states, i.e. by the specific z_i^* such that:

$$NP_i(z_i^*) = U_i \Leftrightarrow z_i^* = \rho U_i \tag{A.1}$$

All agents with $z_i < z_i^*$ participate in the labor market; all those with $z_i > z_i^*$ stay out.

The second discrete choice the agents have to make concerns the labor market state decision: either they accept a job offer or they reject it and continue searching. Again we can identify a threshold: if the productivity and therefore the wage is high enough, they will accept; if not, they will continue searching for a better offer. As before, the threshold is identified by the indifference point between the two alternatives, i.e. by the specific x_{ij}^* such that:

$$U_i = E_{iF}(x_{iF}^*) \quad \Leftrightarrow \quad x_{iF}^* = (1+\tau)\rho U_i \tag{A.2}$$

$$U_i = E_{iI}(x_{iI}^*) \quad \Leftrightarrow \quad x_{iI}^* = \rho U_i + c \tag{A.3}$$

$$U_i = E_{iS}(x_{iS}^*) \quad \Leftrightarrow \quad x_{iS}^* = \rho U_i \tag{A.4}$$

These threshold have a straightforward economic interpretation. Employee jobs require higher productivity to be acceptable than self-employed job because in the first case the worker has to share with the employer. Moreover, the employer has to pay either payroll contributions or illegality costs and therefore the thresholds are increasing in those parameters.

The optimal decision rules and wages schedules can now be incorporated in the value of unemployment defined in equation (2), leading to the following equilibrium equation:

$$
\begin{aligned}
\rho U_i &= b_i + \frac{\beta\lambda_{iF}}{\rho+\delta_{iF}} \int_{(1+\tau)\rho U_i} [x-(1+\tau)\rho U_i]\, dG_{iF}(x) \\
&\quad + \frac{\beta\lambda_{iI}}{\rho+\delta_{iI}} \int_{\rho U_i + c} [x-c-\rho U_i]\, dG_{iI}(x) \\
&\quad + \frac{\lambda_{iS}}{\rho+\delta_{iS}} \int_{\rho U_i} [x-\rho U_i]\, dG_{iS}(x), \quad i = M, W
\end{aligned} \tag{A.5}
$$

The equation is a function of parameters and of the endogenous value of unemployment U_i. Under mild regularity conditions, it admits a unique solution. Given a solution for U_i, all the optimal decisions described in equations (A.1)–(A.4) are fully characterized.

To close the steady state equilibrium, we have to impose that all inflows and outflows in and from each labor market state are equal. The gender specific hazard rate out of unemployment to a job type j is $h_{ij} = \lambda_{ij}\left[1 - G_{ij}(x^*_{ij})\right]$, i.e. the probability of receiving an offer times the probability of accepting the offer. The hazard rate out of employment type j is exogenous and equal to δ_{ij}. By denoting with e_{ij} the proportion of type i agents working in job type j and with u_i the proportion of type i agents searching for a job, the steady state conditions are:

$$\lambda_{iF}\left[1 - G_{iF}(x^*_{iF})\right] u_i = \delta_{iF} e_{iF} \tag{A.6}$$

$$\lambda_{iI}\left[1 - G_{iI}(x^*_{iI})\right] u_i = \delta_{iI} e_{iI} \tag{A.7}$$

$$\lambda_{iS}\left[1 - G_{iF}(x^*_{iS})\right] u_i = \delta_{iS} e_{iS} \tag{A.8}$$

Adding the innocuous normalization that the labor force is measure 1, equations (A.6)–(A.8) produce the following solution:

$$u_i = \frac{\delta_{iF}\delta_{iI}\delta_{iS}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.9}$$

$$e_{iF} = \frac{h_{iF}\delta_{iI}\delta_{iS}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.10}$$

$$e_{iI} = \frac{h_{iI}\delta_{iF}\delta_{iS}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.11}$$

$$e_{iS} = \frac{h_{iS}\delta_{iF}\delta_{iI}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.12}$$

Finally, by denoting with NP_i the proportion of non-participant in the population, we exploit equation (A.1) to find:

$$NP_i = 1 - Q_i(z_i^*) \tag{A.13}$$

We are now ready to provide the following:

Definition 1 ***Equilibrium Definition.***

Given workers' types $i = W, M$ *and employment states' type* $j = F, I, S$*, the vector of parameters* $\{\rho, \lambda_{ij}, \delta_{ij}, b_i, c\}$*, and the probability distribution functions* $\{Q_i(z), G_{ij}(x)\}$ *a* ***search model equilibrium*** *in an economy with formal contribution rate* τ *is a set of values* $\{U_i\}$ *that:*

1. *solves the equilibrium equations* (A.5)*;*

2. *satisfies the steady state conditions* (A.9)–(A.13)*.*

The model is estimated assuming the data are extracted from a steady state defined following Definition 1. Policy and counterfactual will also be performed comparing different steady state at different parameters values. In these experiments, we will use, among others, a measure representing the total output of the labor market. Specifically, we will use two measures of the aggregated average output: the output per worker (Y^{pw}) and the output per-capita (Y^{pc}). The former divides the total production by mass of workers that are currently in a job, while the latter divides the total production by the overall population, including the non-participant. We anticipate here the definitions of these two metrics. For given gender i we define:

$$\begin{aligned} Y_i^{pw} &= \frac{e_{iF}}{1-u_i}\int_{x_{iF}^*} x dG_{iF}(x) + \frac{e_{iI}}{1-u_i}\int_{x_{iI}^*} x dG_{iI}(x) + \frac{e_{iS}}{1-u_i}\int_{x_{iS}^*} x dG_{iS}(x) \\ Y_i^{pc} &= (1-NP_i)\left(e_{iF}\int_{x_{iF}^*} x dG_{iF}(x) + e_{iI}\int_{x_{iI}^*} x dG_{iI}(x) + e_{iS}\int_{x_{iS}^*} x dG_{iS}(x)\right) \end{aligned}$$

They are straightforward averages over the equilibrium measures and distributions of each labor market state in equilibrium.

B Data

We use data from household surveys and employment surveys from five LAC countries: Argentina, Chile, Colombia, and Mexico. In each country, we use the latest available survey leading to survey dates ranging from the third quarter of 2014 to the last quarter of 2016.

In the case of Argentina, we use the *National Survey of Urban Households* (EAHU) conducted in the third quarter of 2014. It is a representative household survey collected by the *National Institute of Statistics and Census* (INDEC) with a cross-sectional structure and reporting information on education, labor force variables and income. In the case of Chile, we use the *National Socio-Economic Characterization Survey* (CASEN) of 2015. It is conducted between November 2015 and January 2016. It is a cross-sectional household survey representative at a national level and reports information on education, labor force, income, and health status. In the case of Colombia, we use the *Great Integrated Household Survey* (GEIH) of the last quarter of 2016. It is a monthly cross-sectional household survey describing labor force status, the quality of life, income and expenditures. Finally, for Mexico we use the *National Occupation and Employment Survey* (ENOE) of the last quarter of 2016. It is a quarterly cross-sectional employment survey focusing on labor markets status and characteristics.

To build the estimation samples, we extract all the individuals aged between 25 and 55 years old and working in non-agricultural activities. Both restrictions are motivated by ensuring a more homogeneous sample of workers. Labor market careers typically exhibit life-cycle patterns. Our approach is not well equipped to capture them and therefore our age restrictions eliminates some of the major life-cycle dynamics (such as retirement concerns or first-entrants).[25] A shorter age range would have guaranteed more homogeneity but the cost in terms of sample size would have been too large, in particular on some countries. The compromise we reached by considering only 25-55 years old generates an age range similar to the one used in comparable literature.[26] The focus on non-agricultural activities is dictated by the theoretical model. Our proposed search model with bargaining is a good – and commonly used – description of labor markets characterized by a clear division of labor and by work for pay. These characteristics are less predominant in the agricultural sectors of most of the countries under consideration and therefore our theoretical model would have not been a good description of them. Nevertheless, it is important to keep in mind that the share of the labor force working in the agricultural sector in Latin America is relevant. In our sample, as can be seen in Table B.1, this is particularly true for male workers with primary education in all countries, with the share of the labor force working in this sector ranging between 20 and 26% in Colombia and Chile, respectively. For women

[25]Incorporating life-cycle effects in search model of the labor market is notoriously problematic and definitely out of the question with the data at our disposal. Two rare exceptions are Bagger et al. (2014) and Pavan (2011), both of which used long and rich panel data to estimate their models.

[26]For example, Bobba et al. (2017) use 35-55 years old; Meghir et al. (2015) 23-65 years old; Flabbi (2010a) 30-55 years old; and Dey and Flinn (2005) 25-54 years old.

with primary education, the share of the agricultural sector drops to a range between 3 and 8% for again Colombia and Chile, respectively. In turn, for secondary education the share of the agricultural sector are considerably lower compared with those of the primary education, being the highest observed in Chile (respectively 9 and 4% for men and women) and Mexico (for men 8%). Finally, as expected, the share of the agricultural sector drops sharply for tertiary education.[27]

We then divide the sample based on the highest level of education completed: primary school or less, secondary school, and tertiary level degree and above. We define four labor market states from the observed data: Unemployed, Formally employed as employee, Informally employed as employee, Self-employed. We also consider the state of no labor market participation. For employed workers we use information about the primary occupation in each sector, formal, informal and self-employment. More than one occupation are not so common in our sample, particularly for primary and secondary education levels. Table B.2 show, the percentage of worker in our sample that have only one occupation, their primary occupation. As can be noticed, at most 3.5 and 5.4% of men and women in primary education, respectively, have more than one occupation (both observed for Argentina), while in secondary education mostly 4% have more than one occupation regardless of gender (again the highest percentages observed for Argentina). For the tertiary education, more occupations are slightly more common, particularly in Argentina and Chile where between 12 and 7% of workers does not have only one occupation.

Following Kanbur (2009) and Levy (2008), we define informal employees as those who are not contributing to the social security system. In most LAC countries, firms are obligated to enroll salaried workers in the social security system and pay contributions which are approximately proportional to wages. Observing this registration in labor market data is considered in the literature a reliable measure of informal employment. Self-employed workers have typically different requirements but they rarely enroll and pay contribution in the system. The overall informal sector is therefore frequently considered the sum of the self-employed and the informal employees (Bobba et al., 2017; Meghir et al., 2015).

When considering women, we also report the presence of young children in the household. We consider two cutoffs based on schooling age: for pre-schoolers we use the cutoff at 5 years of age and for primary and lower-secondary we use the cutoff at 13 age of age. In this way, we are able to identify women with children who are still not old enough to be enrolled in compulsory schooling and women with children who are in the age range typically covered

[27] It is worth to mention that for the case of Argentina, we are not able compute the exact share of the agricultural sector because the survey only covers the urban areas.

by compulsory schooling in the region. Conditioning on the presence of children allows us to capture some of the life-cycle effects that we are forced to ignore given the limitations of our data. We infer the realtionship between children and the adults in our estimation sample in the following way. In the data, we observe the presence and age range of children in the household and the relationship of each household member with the head of household (HH). Crossing this information, we can proxy the child care responsibilities of the women in our sample in the following way. As mentioned, our estimation sample is composed by two sets of adults. The first and by far the largest set is composed by HH and by HH's spouses. In this case, we assume that if a child is the son or daughter of the HH then the HH and the HH's spouse have the main child care responsability of them. The second set is composed by the adult children of HH living at home. We assign childcare responsabilites to these living-at-home adult if in the same household there are grandchildren of the HH.

Finally, our model is constructed to analyze the extensive margin of employment and the determination of hourly wages, leaving out the intensive margin or the determination of hours worked. To have an sense of the relative importance of the contribution of hourly wages, hours worked (the intensive margin) and the probability of being employed the (extensive margin) in the overall wage gap, we make a "fourth-fold" decomposition of the unconditional weekly wage gap in our sample (see for example Daymont and Andrisani, 1984), that is:

$$
\begin{aligned}
W_M^{UNC} - W_W^{UNC} &= W_M P_M - W_W P_W \\
&= w_M h_M P_M - w_W h_W P_W \\
&= (w_M - w_W)\, h_W P_W + (h_M - h_W)\, w_W P_W + (P_M - P_W)\, w_W h_W \\
&\quad + (w_M - w_W)(h_M - h_W)\, P_W + (w_M - w_W)(P_M - P_W)\, h_W \\
&\quad + (h_M - h_W)(P_M - P_W)\, w_W + (w_M - w_W)(h_M - h_W)(P_M - P_W) \\
&= \Delta w + \Delta h + \Delta P + \Delta I
\end{aligned}
$$

where the first term Δw is the pure contribution of the hourly wage gap, the second term Δh is the pure contribution of the weekly hours worked gap, the third term ΔP is the pure contribution of the probability of participating and being employed gap, and finally, the last term ΔI is an interaction term accounting for the fact that differences in w, h and P exist simultaneously between men and women. The results are shown in Table B.3. Two comment are worth to mention. First, the hourly wage gap explain between 24 and 36% of the total gap, while the gap in the probability of being employed account between 18 and 33% of the total gap. These two components, which are captured in our model, account for more than

40% of the total gap. Second, the gap in hourly weekly hours is more relevant for worker with tertiary education; it explain between 18 and 36% of the total gap. For workers with less education levels, primary and secondary, the gap in hours explain at most 11%.

Table B.1: Share of the agricultural sector

	Argentina(*)	Chile	Colombia	Mexico
		Men		
Primary	5.1	25.7	20.1	24.6
Secondary	1.9	9.3	3.9	7.7
Tertiary	1.5	3.5	1.6	1.5
		Women		
Primary	0.5	8.1	3.2	2.3
Secondary	0.1	4.0	0.9	0.7
Tertiary	0.2	1.4	0.4	0.2

(*) Survey covering only urban areas.

Table B.2: Percentage of workers with only one job

	Argentina	Chile	Colombia	Mexico
		Men		
Primary	96.5	97.6	98.9	97.0
Secondary	96.1	97.5	99.0	96.3
Tertiary	87.4	93.1	98.0	94.8
		Women		
Primary	94.8	99.1	98.8	99.0
Secondary	96.0	98.5	98.5	98.3
Tertiary	88.8	95.5	98.6	96.8

Table B.3: Wage differential decomposition

	Argentina	Chile	Colombia	Mexico
Gap due to hourly wages: Δw				
Primary	0.24	0.31	0.27	0.28
Secondary	0.29	0.35	0.31	0.31
Tertiary	0.24	0.36	0.34	0.29
Gap due to weekly hours: Δh				
Primary	0.08	0.04	0.07	0.06
Secondary	0.11	0.06	0.09	0.10
Tertiary	0.36	0.18	0.20	0.27
Gap due to the probability of being employed: ΔP				
Primary	0.18	0.23	0.19	0.20
Secondary	0.22	0.26	0.24	0.23
Tertiary	0.22	0.33	0.32	0.27
Gap due to the interactions: ΔI				
Primary	0.50	0.42	0.47	0.46
Secondary	0.38	0.33	0.36	0.37
Tertiary	0.19	0.14	0.14	0.16

C Likelihood Function

We introduce the notation $k = 1, 2, 3...N_i$ to denote an individual observation in the sample.

The probability of observing an individual k non participating in the labor market is $P(z > z^*)$ (see equation A.13). Given the assumption on the distribution of z, $Q(z)$, and the reservation value of the participation decision, $z^* = \rho U_i$, the contribution to the likelihood of the non participation information is:

$$P_i(k \in NP_i) = 1 - Q(\rho U_i) \tag{C.1}$$

To find the contribution of the unemployment duration information to the likelihood we first define the total hazard rate out of unemployment. Because our model features multi-exits to different types of employment, the total hazard rate out of unemployment is comprised of the different hazards from unemployment to each job type: $h_i = h_{iF} + h_{iI} + h_{iS}$. Each hazard is defined as the probability that a match is formed once an individual meets a potential employer or a self-employment opportunity (see equations A.6–A.8).

The hazard rate, conditional on the model, does not exhibit duration dependence. At the same time, the durations observed in the sample are on-going. As a result, the unemployment duration follows a negative exponential distribution with coefficient equal to the hazard rate. Given that the unemployment duration is observed only for individuals who are actively participating in the labor market and are currently unemployed, the actual likelihood contribution of an unemployed individual k is the joint density of participating ($Q(\rho U_i)$), being unemployed (u_i as defined in equation A.9) and observing a duration $t_{i,k}$, leading to:[28]

$$f_{i,u}(t_{i,k}, k \in U_i, k \notin NP_i) = h_i \exp(-h_i t_{i,k}) u_i Q(\rho U_i) \tag{C.2}$$

To derive the contribution of wages and self-employed income to the likelihood function, it is necessary to take into account three features. First, we have information on wages but not on productivity. Second, the observed wages are those related to matches already formed therefore, in terms of the model, they are accepted wages. Third, we only observe data for those individuals who are currently employed or self-employed.

To take into account these data features, we proceed in the following way. In the first step, we map the unconditional wage cumulative distribution from the unconditional productivity

[28] In the particular case of Argentina, where the structure of the duration data is defined as intervals, the contribution of the unemployment duration information 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.

cumulative distribution ($G_{ij}(x)$) using the wage equations (9)–(10) (for the self-employed, productivity and income coincides). In the second step, we construct the truncated version of the distributions taking into account the optimal decisions rules summarized by the reservation values (x^*_{ij}). In the third step, we use the truncated wages distributions, the probability of participating ($Q(\rho U_i)$) and the probability of being employed (e_{ij} as defined in equations A.10–A.12) to compute the joint density of observed wages. In conclusion, the contributions to the likelihood function for agent k in, respectively, formal employment, informal employment and self-employment are:

$$f_{e_{iF}}(w_{i,k}, w_{i,k} \geq w^*_{iF}, k \in E_{iF}, k \notin NP_i) = \frac{\frac{1+\tau}{\beta} g_{iF}\left(\frac{(1+\tau)(w_{i,k}-(1-\beta)\rho U_i)}{\beta}\right)}{1 - G_{iF}((1+\tau)\rho U_i)} e_{iF} Q(\rho U_i) \quad (C.3)$$

$$f_{e_{iI}}(w_{i,k}, w_{i,k} \geq w^*_{iI}, k \in E_{iI}, k \notin NP_i) = \frac{\frac{1}{\beta} g_{iI}\left(\frac{w_{i,k}+\beta c-(1-\beta)\rho U_i}{\beta}\right)}{1 - G_{iI}(\rho U_i + c)} e_{iI} Q(\rho U_i) \quad (C.4)$$

$$f_{e_{iS}}(w_{i,k}, w_{i,k} \geq w^*_{iS}, k \in E_{iS}, k \notin NP_i) = \frac{g_{iI}(w_{i,k})}{1 - G_{iS}(\rho U_i)} e_{iS} Q(\rho U_i) \quad (C.5)$$

We are now ready to proposed the overall loglikelihood function used to identify and estimate the model:

$$\begin{aligned} \ln L(w_k, t_k, i; \Theta) = & \sum_{i=M,W} \{N_{NP_i} \ln(1 - Q(\rho U_i)) \\ & +(N_{U_i} + N_{E_{iF}} + N_{E_{iI}} + N_{E_{iS}}) \ln Q(\rho U_i) + N_{U_i} \ln h_i \\ & +N_{U_i} \ln u_i + N_{E_{iF}} \ln e_{iF} + N_{E_{iI}} \ln e_{iI} + N_{E_{iS}} \ln e_{iS} \\ & -h_i \sum_{k \in U_i} t_{i,k} + \sum_{k \in F} \ln\left(\frac{\frac{1+\tau}{\beta} g_{iF}\left(\frac{(1+\tau)(w_{i,k}-(1-\beta)\rho U_i)}{\beta}\right)}{1 - G_{iF}((1+\tau)\rho U_i)}\right) \\ & +\sum_{k \in I} \ln\left(\frac{\frac{1}{\beta} g_{iI}\left(\frac{w_{i,k}+\beta c-(1-\beta)\rho U_i}{\beta}\right)}{1 - G_{iI}(\rho U_i + c)}\right) \\ & +\sum_{k \in S} \ln\left(\frac{g_{iI}(w_{i,k})}{1 - G_{iS}(\rho U_i)}\right)\Bigg\} \end{aligned}$$

where $N_{NP_i}, N_{U_i}, N_{E_{iF}}, N_{E_{iI}}, N_{E_{iS}}$ are the sample sizes in each labor market state and Θ is the vector of the primitive parameters of the model.

D Complete Identification Discussion

Since the identification strategy applies in the same way to men and women, in what follows we drop the gender specific index i to reduce notation. Starting with the mobility parameters and taking the first order conditions of the maximization problem of the logarithm of the likelihood function with respect to the hazard rates, we obtain:

$$h_F \quad : \quad \frac{N_U}{h} + \frac{N_U}{u}\partial_{h_F}u + \frac{N_F}{e_F}\partial_{h_F}e_F + \frac{N_I}{e_I}\partial_{h_F}e_I + \frac{N_S}{e_S}\partial_{h_F}e_S - \sum_{k\in U_i} t_k = 0 \tag{D.1}$$

$$h_I \quad : \quad \frac{N_U}{h} + \frac{N_U}{u}\partial_{h_I}u + \frac{N_F}{e_F}\partial_{h_I}e_F + \frac{N_I}{e_I}\partial_{h_I}e_I + \frac{N_S}{e_S}\partial_{h_I}e_S - \sum_{k\in U_i} t_k = 0 \tag{D.2}$$

$$h_S \quad : \quad \frac{N_U}{h} + \frac{N_U}{u}\partial_{h_S}u + \frac{N_F}{e_F}\partial_{h_S}e_F + \frac{N_I}{e_I}\partial_{h_S}e_I + \frac{N_S}{e_S}\partial_{h_S}e_S - \sum_{k\in U_i} t_k = 0 \tag{D.3}$$

and with respect to the arrival rates of termination shocks, we obtain:

$$\delta_F \quad : \quad \frac{N_U}{u}\partial_{\delta_F}u + \frac{N_F}{e_F}\partial_{\delta_F}e_F + \frac{N_I}{e_I}\partial_{\delta_F}e_I + \frac{N_S}{e_S}\partial_{\delta_F}e_S = 0 \tag{D.4}$$

$$\delta_I \quad : \quad \frac{N_U}{u}\partial_{\delta_I}U_i + \frac{N_F}{e_F}\partial_{\delta_I}e_F + \frac{N_I}{e_I}\partial_{\delta_I}e_I + \frac{N_S}{e_S}\partial_{\delta_I}e_S = 0 \tag{D.5}$$

$$\delta_S \quad : \quad \frac{N_U}{u}\partial_{\delta_S}u + \frac{N_F}{e_F}\partial_{\delta_S}e_F + \frac{N_I}{e_I}\partial_{\delta_S}e_I + \frac{N_S}{e_S}\partial_{\delta_S}e_S = 0 \tag{D.6}$$

where $\partial_Y X$ is the partial derivative of the steady state condition X with respect to the parameter Y. Equations (D.1) to (D.6) a system of six nonlinear equations in six unknowns (h_j, δ_j). These parameters are exactly identified if the solution of this system of equations is unique. Given the nonlinearity and issues with empirical identification, we have chosen to follow Bobba et al. (2017) and restrict the set of possible solutions to those that satisfy $\lambda_F = \lambda_I$ and $\delta_F = \delta_I$. The constraints implies that employee jobs share the same arrival and termination rate.

Whit respect to the productivity distributions we assume, as discussed before, that they take a log-normal form. This particular parametrization meets the recoverability condition and belongs to a log location-scale family and therefore the identification of location and the scale of the original distribution should be identified from the location and the scale of the truncated distribution (see Eckstein and van den Berg, 2007, for a detailed discussion). To see this in the context of the distribution of the different types of jobs, we re-parametrize the observed wages distribution for the case of formal jobs in the following way:

$$\frac{\frac{1+\tau}{\beta} g_F\left(\frac{(1+\tau)(w_k-(1-\beta)\rho U)}{\beta}\right)}{1-G_F((1+\tau)\rho U_i)} = \frac{\frac{1}{w_k\sigma_{F,0}}\phi_F\left(\frac{\ln(w_k)-\mu_{F,0}}{\sigma_{F,0}}\right)}{1-\Phi_F\left(\frac{\ln(\rho U_i)-\mu_{F,0}}{\sigma_{F,0}}\right)}$$

where:

$$\mu_{F,0} = (1-\beta)\rho U_i + \frac{\beta}{1+\tau}\mu_F \tag{D.7}$$

$$\sigma_{F,0} = \frac{\beta}{1+\tau}\sigma_F \tag{D.8}$$

that is, $\mu_{F,0}$ and $\sigma_{F,0}$ are the mean (location) and standard deviation (scale) of the observed wages distribution, respectively, and μ_F and σ_F are the mean (location) and standard deviation (scale) of the productivity distribution. From (D.7) and (D.8) it follows immediately that if ρU_i, β and τ are known, then μ_F and σ_F are uniquely identified from the data on wages in the formal sector. The parameters β and τ are set at 0.5 for all countries and at the level of the payroll contributions in each country, respectively. While theoretical identification of β is assured by the model's implications and by the distributional assumptions, its empirical identification is challenging without demand side information[29] and that is why we simply calibrate the parameter to the value of symmetric Nash bargaining. This is definitely a restriction in our context since it force us to the set the same Nash bargaining parameter for men and women. Previous literature has shown that differences in β by gender are likely to be present and they are often interpreted as capturing discrimination or gender-specific attitudes toward negotiation.[30] Even if we have to impose the restriction, it is worth remembering that the presence of endogenous and gender-specific outside options (U_i) still allows the wages to capture differences in bargaining power between men and women. Since the outside option enters directly in the wage equations, a lower outside option for a given gender in a given schooling group translates into lower wages at same productivity compared with the other gender.[31]

Using the same re-parametrization for the observed wages distribution for the case of

[29]For a formal discussion, see Flinn (2006). For an implementation using demand-side information, see Cahuc et al. (2006).

[30]See for example, Bartolucci (2013). Eckstein and Wolpin (1999) and Borowczyk-Martins et al. (2017) are examples of a similar strategy applied to racial gaps instead of gender gaps.

[31]See equations 9 and 10.

informal jobs we have:

$$\frac{\frac{1}{\beta} g_I\left(\frac{w_k+\beta c-(1-\beta)\rho U_i}{\beta}\right)}{1-G_I\left(\rho U_i+c\right)}=\frac{\frac{1}{w_k \sigma_{I,0}} \phi_I\left(\frac{\ln(w_k)-\mu_{I,0}}{\sigma_{I,0}}\right)}{1-\Phi_I\left(\frac{\ln(\rho U_i)-\mu_{I,0}}{\sigma_{I,0}}\right)}$$

where:

$$\mu_{I,0} = (1-\beta)\rho U_i+\beta(\mu_I-c) \tag{D.9}$$

$$\sigma_{I,0} = \beta \sigma_I \tag{D.10}$$

In this case, μ_I and σ_I are uniquely identified from the data if ρU_i, β and c are known, which means that the cost of informality has to be set using additional sources of information in order to be able to identify the productivity distribution in the informal sector. To fix the parameter c, we use the ratio between the cost of informality and the average wage in the formal sector estimated by Bobba et al. (2017) for the case of Mexico and we use that ratio to set this parameter across countries. Finally, the re-parametrization of observed wages distribution for the case of self-employed workers gives:

$$\frac{g_I(w_k)}{1-G_S(\rho U_i)}=\frac{\frac{1}{w_k \sigma_{S,0}} \phi_S\left(\frac{\ln(w_k)-\mu_{S,0}}{\sigma_{S,0}}\right)}{1-\Phi_S\left(\frac{\ln(\rho U_i)-\mu_{S,0}}{\sigma_{S,0}}\right)}$$

where:

$$\mu_{S,0} = \mu_S \tag{D.11}$$

$$\sigma_{S,0} = \sigma_S \tag{D.12}$$

Given that there is no bargaining involved in self-employment, the identification of the location and the scale of the productivity distribution in equations (D.11) and (D.12) is identified one to one from their counterparts in the observed wages distribution provided that ρU_i is known.

To estimate ρU_i, Flinn and Heckman (1982) show that the minimum observed wage is a strongly consistent non parametric estimator of the reservation wage. This estimator is typically used in the literature. However, because an implication of our model is that $w_F(x_F^*) = w_I(x_I^*) = x_I^* = \rho U_i$, the Flinn and Heckman (1982) estimator requires that $\min w_F^o = \min w_I^o = \min w_S^o = \rho U_i$ but nothing guarantees that these equalities hold in the data. Instead, we attempt to estimate ρU_i jointly with all the other parameters maximizing the likelihood function. The problem that arises in this case is that ρU_i determines the reservation productivities, which in turn are the truncation parameters in the accepted wage distributions in all types of job, and changing this parameter in the maximization process of the likelihood function changes its support and violates one of the regularity conditions of the estimation method. To avoid this problem and because it is likely that wages are measured with error (particularly in self-employment), we introduce measurement error in the estimation.

We assumed that the measurement error ϵ is multiplicative, and therefore the observed wage can be expressed as $w^o = w \times \epsilon$. The assumptions we make about the measurement error are threefold: (1) the measurement error is gender specific; (2) we use a log-normal distribution for the measurement error: $v(\epsilon) = \frac{1}{\epsilon\sigma_\epsilon}\phi\left(\frac{\ln\epsilon-\mu_\epsilon}{\sigma_\epsilon}\right)$, where $\phi(\cdot)$ is the standard normal density function, $i = M, W$; and finally (3) we assume that the conditional expectation of the observed wages is equal to the true wages, that is $E[w^o|w] = w$, which implies that $E[\epsilon|w] = 1$. All these assumptions together imply that the parameters μ_ϵ and σ_ϵ satisfy $\sigma_\epsilon = \sqrt{-2\mu_\epsilon}$, and therefore only one parameter of the measurement error has to be estimated. Using the measurement error, the implied density functions of observed wages that should be used in the contributions of wages in all types of jobs to the likelihood function are:

$$f^o_{e_F}(w^o_k) = \int_{\rho U_i} \frac{1}{w} v\left(\frac{w^o_k}{w}\right) f_{e_F}(w, w \geq \rho U_i, k \in F, k \notin NP_i)dw \tag{D.13}$$

$$f^o_{e_I}(w^o_k) = \int_{\rho U_i} \frac{1}{w} v\left(\frac{w^o_k}{w}\right) f_{e_I}(w, w \geq w^*_I, k \in I, k \notin NP_i)dw \tag{D.14}$$

$$f^o_{e_S}(w^o_k) = \int_{\rho U_i} \frac{1}{w} v\left(\frac{w^o_k}{w}\right) f_{e_S}(w, w \geq w^*_S, k \in S, k \notin NP_i)dw \tag{D.15}$$

Finally, to identify the parameter γ in $Q(z)$, the assumed distribution is required to be invertible with respect to its parameter, and the negative exponential distribution meets this requirement. The first order condition of the maximum likelihood estimation gives the following estimator for this parameter:

$$\gamma = \frac{\ln\left(\frac{N}{N_{NP_i}}\right)}{\rho U_i}$$

where N is the total number of individuals and N_{NP_i} is the number of individuals who are not participating in the labor market. To analyze the influence of the presence of kids in the household on the participation rates (in particular in the γ parameter), we divided those non participating individuals into three groups. First those that have kids 5 years old or younger in the household ($k5$), second, those that have kids between 5 and 13 years old ($k13$), and third the remaining non participants (*other*). It can be shown that if $\Pr[NP_i \cap k5] + \Pr[NP_i \cap k13] + \Pr[NP_i \cap other] = \Pr[NP_i]$, the estimator of the parameter γ by group is:

$$\gamma_\kappa = \frac{\ln\left(\frac{N_\kappa}{N_{\kappa,NP_i}}\right)}{\rho U_i}$$

where N_κ is the total number of individuals in the group κ and N_{κ,NP_i} is the number of individuals who are not participating in the group κ.

E Complete Estimation Results

Tables E.1, E.6, E.11, and E.16 report the complete set of descriptive statistics for each country, gender and education group.

Tables E.2, E.7, E.12, and E.17 report the estimated structural parameters of the model for each country, gender and education group.

Tables E.3, E.8, E.13, and E.18, report the implications for the labor market dynamics and the distribution across labor market states, while tables E.4, E.9, E.14, and E.19, report the implications for wages and productivity.

As mentioned in the main text, we perform various policy experiments. Tables E.5, E.10, E.15, and E.20, report the impact of the policy experiments on a variety of labor market outcomes together with the same outcomes reported at benchmark.

Table E.1: Argentina - Descriptive Statistics

Labor Market States	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w
	Men					Women				
Education Group: Primary										
Unemployed	400	0.05	2.78	-	-	311	0.04	3.33	-	-
Formal Emp.	2594	0.34	-	4.49	2.14	1070	0.14	-	3.78	1.75
Informal Emp.	1773	0.24	-	2.48	1.33	1584	0.21	-	2.60	1.56
Self-Emp.	2030	0.27	-	3.00	2.27	726	0.10	-	2.37	2.18
Non Part.	737	0.10	-	-	-	3946	0.52	-	-	-
$K \leq 5$						1750	0.44			
$5 < K \leq 13$						1091	0.28			
Education Group: Secondary										
Unemployed	190	0.04	3.02	-	-	219	0.05	3.58	-	-
Formal Emp.	2460	0.54	-	5.10	2.36	1426	0.30	-	4.66	2.19
Informal Emp.	665	0.14	-	2.84	1.65	712	0.15	-	2.78	1.78
Self-Emp.	1043	0.23	-	3.52	2.77	565	0.12	-	3.16	3.21
Non Part.	229	0.05	-	-	-	1837	0.39	-	-	-
$K \leq 5$						772	0.42			
$5 < K \leq 13$						485	0.26			
Education Group: Tertiary										
Unemployed	140	0.03	3.29	-	-	252	0.04	3.63	-	-
Formal Emp.	2555	0.59	-	6.73	3.35	3455	0.53	-	6.64	3.03
Informal Emp.	374	0.09	-	4.17	2.96	640	0.10	-	3.89	2.77
Self-Emp.	914	0.21	-	5.21	4.36	812	0.12	-	5.23	4.77
Non Part.	335	0.08	-	-	-	1344	0.21	-	-	-
$K \leq 5$						506	0.38			
$5 < K \leq 13$						292	0.22			

Note: Wage distributions are trimmed at the top and bottom 1 percentile by gender, education group and type of job, and are reported in US Dollars of December 2016 (Exchange Rate = 15.8620 Argentinian Pesos/US). A worker is categorized as informal if he/she reports not having benefits of social security. K means proportion of women with the presence of kids in the household with respect to non participating women. Unemployment durations ($\bar{t}_u$) are only observed in time intervals.

Table E.2: Argentina - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	0.2010	0.1482	1.7532	1.4020	1.8743	1.6045
	(0.0452)	(0.0772)	(0.0548)	(0.0518)	(0.0776)	(0.0725)
λ_F	0.1291	0.1270	0.2148	0.1824	0.2090	0.2009
	(0.0064)	(0.0047)	(0.0113)	(0.0051)	(0.0104)	(0.0055)
λ_S	0.0991	0.0492	0.1435	0.1192	0.0857	0.0498
	(0.0158)	(0.0060)	(0.0188)	(0.0800)	(0.0041)	(0.0021)
δ_F	0.0235	0.0298	0.0166	0.0286	0.0115	0.0147
	(0.0010)	(0.0011)	(0.0009)	(0.0008)	(0.0006)	(0.0004)
δ_S	0.0194	0.0212	0.0106	0.0056	0.0100	0.0115
	(0.0012)	(0.0026)	(0.0012)	(0.0011)	(0.0003)	(0.0005)
μ_F	2.5652	2.3973	2.5337	2.4788	2.8458	2.8579
	(0.0120)	(0.0214)	(0.0123)	(0.0133)	(0.0123)	(0.0104)
σ_F	0.0055	0.0056	0.0023	0.0044	0.0015	0.0012
	(0.0014)	(0.0093)	(0.0015)	(0.0014)	(0.0007)	(0.0007)
μ_I	1.6267	1.6492	0.2906	0.7026	-0.8272	-0.7052
	(0.0107)	(0.0222)	(0.0491)	(0.0215)	(0.1035)	(0.0833)
σ_I	0.2555	0.3702	0.8894	0.8819	1.6085	1.6250
	(0.0235)	(0.0189)	(0.0484)	(0.0360)	(0.0765)	(0.0628)
μ_S	0.9628	0.6249	0.3672	-1.1564	1.1741	1.0537
	(0.1716)	(0.0316)	(0.2615)	(0.7305)	(0.0767)	(0.1031)
σ_S	0.5374	0.7032	0.8134	1.2797	0.7675	0.8914
	(0.0575)	(0.0279)	(0.0769)	(0.1621)	(0.0412)	(0.0511)
σ_{ME}	0.4533	0.4495	0.4626	0.4834	0.4778	0.4574
	(0.0066)	(0.0106)	(0.0057)	(0.0086)	(0.0060)	(0.0057)
γ	11.5653	4.4566	1.7096	0.6789	1.3640	0.9826
γ_{k5}	-	3.6063	-	0.5685	-	0.8184
γ_{k13}	-	4.7796	-	0.7131	-	1.0216
γ_{other}	-	5.3355	-	0.7786	-	1.0859
b	-16.2900	-12.0563	-14.1630	-10.3558	-22.8976	-21.3658
c	0.4717	0.4717	0.5350	0.5350	0.4710	0.4710
$LogLikelihood$	-21279	-11291	-13751	-9427	-13581	-17417
N	7534	7637	4587	4759	4318	6503

Note: Bootstrap standard errors (based on 100 replications) in parenthesis. Non estimated parameters: $\beta = 0.5$, $\tau = 0.48$ and $\rho = 0.062$.

Table E.3: Argentina - Labor Market Dynamics and States

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
h_u									
Data	-	-	-	-	-	-	-	-	-
Model	0.357	0.303	0.849	0.331	0.292	0.880	0.304	0.276	0.906
$h_{u \to e_F}$									
Model	0.129	0.127	0.984	0.215	0.183	0.850	0.208	0.201	0.965
$h_{u \to e_I}$									
Model	0.129	0.127	0.984	0.059	0.095	1.616	0.031	0.038	1.227
$h_{u \to e_S}$									
Model	0.099	0.049	0.497	0.058	0.014	0.249	0.065	0.037	0.565
u									
Data	0.053	0.041	0.767	0.041	0.046	1.111	0.032	0.039	1.195
Model	0.058	0.084	1.444	0.044	0.075	1.732	0.035	0.049	1.389
e_F									
Data	0.344	0.140	0.407	0.536	0.300	0.559	0.592	0.531	0.898
Model	0.321	0.360	1.119	0.563	0.481	0.854	0.640	0.668	1.043
e_I									
Data	0.235	0.207	0.881	0.145	0.150	1.032	0.087	0.098	1.136
Model	0.321	0.360	1.119	0.154	0.249	1.622	0.095	0.126	1.327
e_S									
Data	0.269	0.095	0.353	0.227	0.119	0.522	0.212	0.125	0.590
Model	0.299	0.196	0.657	0.239	0.194	0.811	0.229	0.157	0.686
np									
Data	0.098	0.517	5.282	0.050	0.386	7.732	0.078	0.207	2.664
Model	0.098	0.517	5.282	0.050	0.386	7.732	0.078	0.207	2.664

Table E.4: Argentina - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	13.004	10.994	0.845	12.601	11.927	0.947	17.218	17.425	1.012
$SD(x_F)$									
Model	0.072	0.061	0.847	0.035	0.052	1.502	0.026	0.016	0.614
$E[x_I]$									
Model	5.256	5.572	1.060	1.986	2.979	1.500	1.595	1.850	1.160
$SD[x_I]$									
Model	1.365	2.136	1.565	2.181	3.231	1.482	5.608	6.678	1.191
$E[x_S]$									
Model	3.026	2.392	0.791	2.009	0.714	0.355	4.351	4.267	0.981
$SD[x_S]$									
Model	1.751	1.913	1.093	1.946	1.453	0.747	3.889	4.702	1.209
Y_W									
Model	7.192	7.020	0.976	9.027	8.152	0.903	13.448	13.884	1.032
Y_C									
Model	6.109	3.106	0.508	8.203	4.628	0.564	11.968	10.477	0.875
$E[w\|e_F]$									
Data	4.492	3.783	0.842	5.095	4.662	0.915	6.728	6.642	0.987
Model	4.523	3.768	0.833	5.161	4.761	0.922	6.749	6.700	0.993
$SD[w\|e_F]$									
Data	2.140	1.749	0.817	2.361	2.189	0.927	3.354	3.035	0.905
Model	2.169	1.773	0.818	2.541	2.448	0.963	3.443	3.230	0.938
$E[w\|e_I]$									
Data	2.477	2.597	1.048	2.845	2.783	0.978	4.167	3.892	0.934
Model	2.504	2.641	1.055	2.853	2.779	0.974	4.843	4.364	0.901
$SD[w\|e_I]$									
Data	1.329	1.559	1.173	1.645	1.782	1.083	2.957	2.774	0.938
Model	1.420	1.741	1.227	2.430	2.344	0.964	14.675	6.817	0.465
$E[w\|e_S]$									
Data	2.997	2.365	0.789	3.520	3.156	0.897	5.207	5.228	1.004
Model	3.028	2.421	0.800	3.526	3.196	0.906	5.246	5.492	1.047
$SD[w\|e_S$									
Data	2.269	2.184	0.962	2.771	3.206	1.157	4.360	4.770	1.094
Model	2.477	2.334	0.942	3.053	3.515	1.151	4.979	6.201	1.245

Note: $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, Y_W is the output per worker, Y_C is the output per capita, $E[w|e]$ is the average wage conditional on the employment status e, and finally $SD[w|e]$ is the standard deviation of wages conditioning in the employment status e.

Table E.5: Argentina - Policy Experiments

	Benchmark			Policy Exp. 1		Policy Exp. 2	
	M	W	W/M	W	W/M	W	W/M
				Primary			
u	0.058	0.084	1.444	0.084	1.444	0.085	1.449
e_F	0.321	0.360	1.119	0.360	1.119	0.361	1.123
e_I	0.321	0.360	1.119	0.360	1.119	0.361	1.123
e_S	0.299	0.196	0.657	0.196	0.657	0.194	0.648
np	0.098	0.517	5.282	0.422	4.312	0.091	0.930
h_u	0.357	0.303	0.849	0.303	0.849	0.302	0.847
Y_W	7.192	7.020	0.976	7.020	0.976	7.749	1.077
Y_C	6.109	3.106	0.508	3.716	0.608	6.448	1.055
$E[w\|e_F]$	4.494	3.788	0.843	3.788	0.843	4.354	0.969
$E[w\|e_I]$	1.876	1.957	1.043	1.957	1.043	2.340	1.247
$E[w\|e_S]$	1.123	0.882	0.786	0.882	0.786	1.171	1.043
Res. W.	0.201	0.148	0.736	0.148	0.736	0.538	2.674
				Secondary			
u	0.044	0.075	1.732	0.075	1.732	0.080	1.836
e_F	0.563	0.481	0.854	0.481	0.854	0.510	0.905
e_I	0.154	0.249	1.622	0.249	1.622	0.250	1.623
e_S	0.239	0.194	0.811	0.194	0.811	0.161	0.671
np	0.050	0.386	7.732	0.297	5.947	0.285	5.708
h_u	0.331	0.292	0.880	0.292	0.880	0.283	0.854
Y_W	9.027	8.152	0.903	8.152	0.903	9.371	1.038
Y_C	8.203	4.628	0.564	5.299	0.646	6.165	0.752
$E[w\|e_F]$	5.133	4.731	0.922	4.731	0.922	5.357	1.044
$E[w\|e_I]$	2.382	2.299	0.965	2.299	0.965	2.705	1.136
$E[w\|e_S]$	2.077	1.782	0.858	1.782	0.858	2.221	1.069
Res. W.	1.753	1.402	0.800	1.402	0.800	1.849	1.055
				Tertiary			
u	0.035	0.049	1.389	0.049	1.389	0.051	1.440
e_F	0.640	0.668	1.043	0.668	1.043	0.692	1.081
e_I	0.095	0.126	1.327	0.126	1.327	0.112	1.176
e_S	0.229	0.157	0.686	0.157	0.686	0.146	0.635
np	0.078	0.207	2.664	0.150	1.931	0.101	1.301
h_u	0.304	0.276	0.906	0.276	0.906	0.266	0.875
Y_W	13.448	13.884	1.032	13.884	1.032	15.733	1.170
Y_C	11.968	10.477	0.875	11.228	0.938	13.430	1.122
$E[w\|e_F]$	6.753	6.571	0.973	6.571	0.973	7.513	1.112
$E[w\|e_I]$	3.533	3.358	0.950	3.358	0.950	4.234	1.198
$E[w\|e_S]$	2.729	2.624	0.961	2.624	0.961	3.307	1.212
Res. W.	1.873	1.604	0.857	1.604	0.857	2.334	1.246

Table E.5: Argentina - Policy Experiments – continued from previous page

	Policy Exp. 3		Policy Exp. 4 ($\tau = 0$)		Policy Exp. 4 ($c = 0$)	
	W	W/M	W	W/M	W	W/M
			Primary			
u	0.084	1.444	0.084	1.444	0.084	1.445
e_F	0.360	1.119	0.360	1.119	0.360	1.120
e_I	0.360	1.119	0.360	1.119	0.360	1.120
e_S	0.196	0.657	0.196	0.657	0.196	0.656
np	0.506	5.175	0.480	6.151	0.333	9.308
h_u	0.303	0.849	0.303	0.849	0.303	0.849
Y_W	7.020	0.976	7.020	0.976	7.023	0.976
Y_C	3.174	0.520	3.342	0.535	4.290	0.657
$E[w\|e_F]$	4.191	0.933	5.579	0.844	3.838	0.846
$E[w\|e_I]$	2.162	1.152	2.868	1.047	2.006	1.045
$E[w\|e_S]$	0.972	0.865	1.279	0.788	0.933	0.800
Res. W.	0.153	0.759	0.165	0.746	0.247	0.856
			Secondary			
u	0.077	1.765	0.081	1.713	0.073	1.741
e_F	0.490	0.870	0.514	0.844	0.463	0.858
e_I	0.247	1.605	0.238	1.745	0.293	1.479
e_S	0.186	0.778	0.167	0.804	0.172	0.777
np	0.369	7.392	0.325	11.572	0.362	7.962
h_u	0.288	0.869	0.279	0.901	0.311	0.891
Y_W	8.287	0.918	8.637	0.898	7.896	0.906
Y_C	4.827	0.588	5.357	0.601	4.671	0.586
$E[w\|e_F]$	5.198	1.013	6.790	0.925	4.778	0.926
$E[w\|e_I]$	2.535	1.064	3.350	0.960	2.162	0.983
$E[w\|e_S]$	1.973	0.950	2.634	0.871	1.882	0.885
Res. W.	1.468	0.838	1.654	0.792	1.496	0.828
			Tertiary			
u	0.049	1.401	0.050	1.383	0.048	1.380
e_F	0.674	1.052	0.689	1.038	0.651	1.035
e_I	0.122	1.291	0.114	1.333	0.150	1.321
e_S	0.155	0.674	0.147	0.685	0.152	0.679
np	0.190	2.446	0.149	3.166	0.200	2.667
h_u	0.273	0.898	0.267	0.910	0.284	0.913
Y_W	13.994	1.041	14.289	1.029	13.562	1.025
Y_C	10.779	0.901	11.549	0.906	10.336	0.875
$E[w\|e_F]$	7.237	1.072	9.508	0.977	6.589	0.974
$E[w\|e_I]$	3.752	1.062	5.137	0.957	3.025	0.943
$E[w\|e_S]$	2.902	1.063	3.863	0.976	2.655	0.965
Res. W.	1.691	0.903	1.939	0.866	1.639	0.863

Table E.6: Chile - Descriptive Statistics

Labor Market States	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w
	Men					Women				
Education Group: Primary										
Unemployed	873	0.07	2.55	-	-	776	0.05	2.09	-	-
Formal Emp.	5807	0.46	-	2.68	1.11	2703	0.17	-	2.13	0.68
Informal Emp.	865	0.07	-	2.31	1.12	403	0.03	-	2.00	1.38
Self-Emp.	3073	0.25	-	2.63	2.02	1871	0.12	-	2.33	2.29
Non Part.	1882	0.15	-	-	-	10176	0.64	-	-	-
$K \leq 5$						3201	0.31			
$5 < K \leq 13$						2710	0.27			
Education Group: Secondary										
Unemployed	1002	0.07	2.89	-	-	980	0.05	2.67	-	-
Formal Emp.	9995	0.65	-	3.26	1.58	7052	0.39	-	2.57	1.04
Informal Emp.	715	0.05	-	2.80	1.71	531	0.03	-	2.37	1.56
Self-Emp.	2717	0.18	-	3.46	3.11	2203	0.12	-	2.84	2.76
Non Part.	892	0.06	-	-	-	7504	0.41	-	-	-
$K \leq 5$						3067	0.41			
$5 < K \leq 13$						2071	0.28			
Education Group: Tertiary										
Unemployed	778	0.06	3.35	-	-	802	0.05	2.93	-	-
Formal Emp.	8510	0.66	-	7.31	5.92	9246	0.60	-	5.50	3.73
Informal Emp.	446	0.03	-	5.73	5.46	497	0.03	-	4.98	3.79
Self-Emp.	1966	0.15	-	8.09	9.04	1442	0.09	-	6.20	6.67
Non Part.	1278	0.10	-	-	-	3401	0.22	-	-	-
$K \leq 5$						1314	0.39			
$5 < K \leq 13$						769	0.23			

Note: Wage distributions are trimmed at the top and bottom 1 percentile by gender, education group and type of job, and are reported in US Dollars of December 2016 (Exchange Rate = 667.17 Chilean Pesos/US). A worker is categorized as informal if he/she reports not having benefits of social security. K means proportion of women with the presence of kids in the household with respect to non participating women.

Table E.7: Chile - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	1.1619	0.1351	1.6532	0.9071	3.2588	2.1330
	(0.0422)	(0.0091)	(0.0347)	(0.0486)	(0.5782)	(0.0835)
λ_F	0.2184	0.1394	0.2759	0.2430	0.2085	0.2460
	(0.0137)	(0.0105)	(0.0205)	(0.0234)	(0.0172)	(0.0167)
λ_S	0.2083	0.2016	0.4518	0.2619	0.1850	0.1993
	(0.0176)	(0.0099)	(0.1680)	(0.0156)	(0.0362)	(0.0209)
δ_F	0.0330	0.0697	0.0277	0.0349	0.0191	0.0213
	(0.0021)	(0.0052)	(0.0021)	(0.0039)	(0.0016)	(0.0014)
δ_S	0.0398	0.0836	0.0186	0.0449	0.0313	0.0454
	(0.0020)	(0.0041)	(0.0053)	(0.0033)	(0.0043)	(0.0039)
μ_F	1.6253	1.5930	1.7619	1.6358	2.5841	2.3593
	(0.0119)	(0.0071)	(0.0092)	(0.0105)	(0.0720)	(0.0127)
σ_F	0.0029	0.0829	0.0050	0.0042	0.1405	0.0109
	(0.0014)	(0.0071)	(0.0035)	(0.0011)	(0.2957)	(0.0027)
μ_I	-1.0825	1.3222	-1.2456	-1.6818	-1.1494	-2.3260
	(0.0936)	(0.0214)	(0.1011)	(0.4031)	(0.7627)	(0.1911)
σ_I	1.4107	0.4296	1.3244	1.5077	1.5277	2.0542
	(0.0661)	(0.0308)	(0.0612)	(0.2120)	(0.3560)	(0.1038)
μ_S	0.4615	0.5272	-0.9611	-0.4041	1.0008	0.4947
	(0.0866)	(0.0194)	(0.5700)	(0.1616)	(0.2676)	(0.2191)
σ_S	0.7044	0.8061	1.2033	1.2337	0.9903	1.1606
	(0.0326)	(0.0174)	(0.1232)	(0.0861)	(0.1027)	(0.0751)
σ_{ME}	0.3943	0.2839	0.4271	0.3714	0.6751	0.5976
	(0.0045)	(0.0055)	(0.0030)	(0.0049)	(0.1280)	(0.0037)
γ	1.6295	3.3172	1.7200	0.9809	0.7113	0.7077
γ_{k5}	-	3.0759	-	0.8302	-	0.6117
γ_{k13}	-	3.5540	-	1.0149	-	0.7252
γ_{other}	-	3.3424	-	1.1237	-	0.7782
b	-5.2218	-7.1410	-5.2652	-6.1237	-12.5334	-12.7475
c	0.2809	0.2809	0.3425	0.3425	0.5119	0.5119
$LogLikelihood$	-28044	-15330	-38209	-26514	-42153	-38439
N	12500	15929	15321	18270	12978	15388

Note: Bootstrap standard errors (based on 100 replications) in parenthesis. Non estimated parameters: $\beta = 0.5$, $\tau = 0.20$ and $\rho = 0.067$.

Table E.8: Chile - Labor Market Dynamics and States

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
h_u									
Data	0.391	0.479	1.225	0.346	0.375	1.082	0.299	0.341	1.142
Model	0.392	0.480	1.226	0.346	0.373	1.078	0.299	0.341	1.142
$h_{u \to e_F}$									
Model	0.218	0.139	0.638	0.275	0.243	0.882	0.209	0.246	1.179
$h_{u \to e_I}$									
Model	0.033	0.139	4.192	0.020	0.025	1.268	0.011	0.013	1.216
$h_{u \to e_S}$									
Model	0.140	0.201	1.438	0.051	0.105	2.061	0.079	0.082	1.036
u									
Data	0.070	0.049	0.698	0.065	0.054	0.820	0.060	0.052	0.869
Model	0.082	0.135	1.640	0.069	0.091	1.306	0.066	0.067	1.006
e_F									
Data	0.465	0.170	0.365	0.652	0.386	0.592	0.656	0.601	0.916
Model	0.545	0.270	0.495	0.692	0.632	0.912	0.727	0.771	1.060
e_I									
Data	0.069	0.025	0.366	0.047	0.029	0.623	0.034	0.032	0.940
Model	0.083	0.270	3.252	0.050	0.065	1.310	0.038	0.042	1.094
e_S									
Data	0.246	0.117	0.478	0.177	0.121	0.680	0.151	0.094	0.619
Model	0.289	0.325	1.124	0.188	0.213	1.129	0.168	0.120	0.716
np									
Data	0.151	0.639	4.243	0.058	0.411	7.055	0.098	0.221	2.244
Model	0.151	0.639	4.243	0.058	0.411	7.055	0.098	0.221	2.244

Table E.9: Chile - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	5.081	4.936	0.971	5.824	5.134	0.881	13.383	10.585	0.791
$SD(x_F)$									
Model	0.015	0.410	27.215	0.030	0.021	0.719	1.887	0.115	0.061
$E[x_I]$									
Model	0.916	4.115	4.492	0.692	0.580	0.838	1.018	0.806	0.792
$SD[x_I]$									
Model	2.304	1.852	0.804	1.512	1.711	1.131	3.111	6.593	2.120
$E[x_S]$									
Model	2.039	2.345	1.150	0.797	1.429	1.793	4.441	3.217	0.724
$SD[x_S]$									
Model	1.629	2.243	1.377	1.431	2.706	1.891	5.735	5.426	0.946
Y_W									
Model	4.209	3.706	0.881	5.269	4.502	0.854	12.272	10.028	0.817
Y_C									
Model	3.281	1.158	0.353	4.618	2.412	0.522	10.328	7.289	0.706
$E[w\|e_F]$									
Data	2.676	2.126	0.794	3.262	2.566	0.787	7.312	5.501	0.752
Model	2.714	2.142	0.789	3.269	2.603	0.796	7.229	5.493	0.760
$SD[w\|e_F]$									
Data	1.107	0.679	0.613	1.577	1.039	0.659	5.921	3.730	0.630
Model	1.118	0.663	0.593	1.475	1.003	0.680	5.664	3.596	0.635
$E[w\|e_I]$									
Data	2.315	2.004	0.866	2.798	2.372	0.848	5.730	4.983	0.870
Model	2.419	1.969	0.814	2.824	1.956	0.692	5.797	5.426	0.936
$SD[w\|e_I]$									
Data	1.122	1.381	1.232	1.707	1.560	0.914	5.458	3.787	0.694
Model	2.737	1.088	0.398	2.545	2.179	0.856	6.522	8.316	1.275
$E[w\|e_S]$									
Data	2.632	2.328	0.885	3.457	2.842	0.822	8.091	6.199	0.766
Model	2.655	2.363	0.890	3.420	2.916	0.853	8.127	6.534	0.804
$SD[w\|e_S$									
Data	2.020	2.289	1.133	3.110	2.764	0.889	9.040	6.670	0.738
Model	2.143	2.491	1.163	3.307	3.827	1.157	10.397	9.254	0.890

Note: $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, Y_W is the output per worker, Y_C is the output per capita, $E[w|e]$ is the average wage conditional on the employment status e, and finally $SD[w|e]$ is the standard deviation of wages conditioning in the employment status e.

Table E.10: Chile - Policy Experiments

	Benchmark			Policy Exp. 1		Policy Exp. 2	
	M	W	W/M	W	W/M	W	W/M
				Primary			
u	0.082	0.135	1.640	0.135	1.640	0.135	1.646
e_F	0.545	0.270	0.495	0.270	0.495	0.271	0.497
e_I	0.083	0.270	3.252	0.270	3.252	0.271	3.264
e_S	0.289	0.325	1.124	0.325	1.124	0.323	1.115
np	0.151	0.639	4.243	0.571	3.789	0.303	2.016
h_u	0.392	0.480	1.226	0.480	1.226	0.478	1.220
Y_W	4.209	3.706	0.881	3.706	0.881	4.093	0.973
Y_C	3.281	1.158	0.353	1.377	0.420	2.465	0.751
$E[w\|e_F]$	2.698	2.124	0.787	2.124	0.787	2.442	0.905
$E[w\|e_I]$	2.209	1.782	0.807	1.782	0.807	2.066	0.935
$E[w\|e_S]$	1.685	1.045	0.620	1.045	0.620	1.266	0.752
Res. W.	1.161	0.135	0.116	0.135	0.116	0.359	0.310
				Secondary			
u	0.069	0.091	1.306	0.091	1.306	0.093	1.333
e_F	0.692	0.632	0.912	0.632	0.912	0.645	0.931
e_I	0.050	0.065	1.310	0.065	1.310	0.061	1.225
e_S	0.188	0.213	1.129	0.213	1.129	0.202	1.070
np	0.058	0.411	7.055	0.322	5.529	0.322	5.535
h_u	0.346	0.373	1.078	0.373	1.078	0.364	1.050
Y_W	5.269	4.502	0.854	4.502	0.854	5.015	0.952
Y_C	4.618	2.412	0.522	2.776	0.601	3.085	0.668
$E[w\|e_F]$	3.253	2.593	0.797	2.593	0.797	2.930	0.901
$E[w\|e_I]$	2.612	1.849	0.708	1.849	0.708	2.136	0.818
$E[w\|e_S]$	2.280	1.695	0.743	1.695	0.743	1.986	0.871
Res. W.	1.653	0.907	0.549	0.907	0.549	1.154	0.698
				Tertiary			
u	0.066	0.067	1.006	0.067	1.006	0.068	1.017
e_F	0.727	0.771	1.060	0.771	1.060	0.780	1.072
e_I	0.038	0.042	1.094	0.042	1.094	0.039	1.026
e_S	0.168	0.120	0.716	0.120	0.716	0.114	0.676
np	0.098	0.221	2.244	0.159	1.612	0.150	1.523
h_u	0.299	0.341	1.142	0.341	1.142	0.335	1.121
Y_W	12.272	10.028	0.817	10.028	0.817	11.099	0.904
Y_C	10.328	7.289	0.706	7.871	0.762	8.797	0.852
$E[w\|e_F]$	7.206	5.477	0.760	5.477	0.760	6.192	0.859
$E[w\|e_I]$	5.370	5.238	0.975	5.238	0.975	6.061	1.129
$E[w\|e_S]$	5.051	3.760	0.744	3.760	0.744	4.377	0.867
Res. W.	3.259	2.133	0.655	2.133	0.655	2.681	0.823

Table E.10: Chile - Policy Experiments – continued from previous page

	Policy Exp. 3		Policy Exp. 4 ($\tau = 0$)		Policy Exp. 4 ($c = 0$)	
	W	W/M	W	W/M	W	W/M
			Primary			
u	0.135	1.640	0.135	1.611	0.135	1.670
e_F	0.270	0.495	0.270	0.486	0.270	0.504
e_I	0.270	3.252	0.270	3.371	0.270	2.667
e_S	0.325	1.124	0.325	1.158	0.325	1.153
np	0.636	4.226	0.630	4.705	0.557	3.782
h_u	0.480	1.226	0.480	1.252	0.480	1.204
Y_W	3.706	0.881	3.706	0.869	3.708	0.893
Y_C	1.166	0.355	1.186	0.350	1.421	0.437
$E[w\|e_F]$	2.233	0.828	2.537	0.804	2.145	0.793
$E[w\|e_I]$	1.873	0.848	2.127	0.806	1.803	0.899
$E[w\|e_S]$	1.097	0.651	1.243	0.629	1.067	0.629
Res. W.	0.136	0.117	0.139	0.113	0.177	0.150
			Secondary			
u	0.091	1.312	0.092	1.289	0.089	1.292
e_F	0.634	0.916	0.642	0.901	0.617	0.902
e_I	0.064	1.293	0.062	1.358	0.089	1.407
e_S	0.210	1.116	0.204	1.198	0.205	1.114
np	0.403	6.924	0.385	8.618	0.405	7.099
h_u	0.371	1.072	0.366	1.083	0.382	1.087
Y_W	4.520	0.858	4.563	0.849	4.417	0.845
Y_C	2.452	0.531	2.549	0.535	2.395	0.522
$E[w\|e_F]$	2.715	0.834	3.054	0.800	2.600	0.798
$E[w\|e_I]$	1.948	0.746	2.227	0.701	1.586	0.664
$E[w\|e_S]$	1.785	0.783	2.036	0.736	1.713	0.747
Res. W.	0.926	0.560	0.974	0.539	0.921	0.553
			Tertiary			
u	0.067	1.009	0.068	1.002	0.066	1.004
e_F	0.774	1.063	0.780	1.056	0.764	1.059
e_I	0.041	1.076	0.039	1.113	0.051	1.109
e_S	0.118	0.704	0.113	0.715	0.119	0.714
np	0.213	2.162	0.194	2.363	0.219	2.242
h_u	0.339	1.136	0.335	1.146	0.344	1.143
Y_W	10.054	0.819	10.119	0.815	9.956	0.816
Y_C	7.383	0.715	7.608	0.716	7.260	0.706
$E[w\|e_F]$	5.735	0.796	6.453	0.764	5.483	0.760
$E[w\|e_I]$	5.547	1.033	6.422	0.990	4.661	0.935
$E[w\|e_S]$	3.966	0.785	4.547	0.752	3.775	0.746
Res. W.	2.186	0.671	2.320	0.660	2.145	0.656

Table E.11: Colombia - Descriptive Statistics

Labor Market States	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w
	Men					Women				
Education Group: Primary										
Unemployed	607	0.06	3.14	-	-	828	0.07	4.56	-	-
Formal Emp.	1784	0.18	-	1.31	0.41	669	0.06	-	1.17	0.23
Informal Emp.	1311	0.13	-	1.08	0.39	935	0.08	-	0.87	0.36
Self-Emp.	5487	0.55	-	1.12	0.66	4199	0.35	-	0.80	0.57
Non Part.	758	0.08	-	-	-	5429	0.45	-	-	-
$K \leq 5$						1870	0.34			
$5 < K \leq 13$						1552	0.29			
Education Group: Secondary										
Unemployed	577	0.06	4.05	-	-	984	0.09	5.22	-	-
Formal Emp.	3656	0.41	-	1.45	0.54	2246	0.21	-	1.31	0.38
Informal Emp.	819	0.09	-	1.13	0.41	932	0.09	-	0.98	0.35
Self-Emp.	3496	0.39	-	1.40	0.91	3084	0.29	-	1.07	0.84
Non Part.	408	0.05	-	-	-	3335	0.32	-	-	-
$K \leq 5$						1272	0.38			
$5 < K \leq 13$						970	0.29			
Education Group: Tertiary										
Unemployed	840	0.09	5.33	-	-	1611	0.12	6.02	-	-
Formal Emp.	4551	0.50	-	3.06	2.24	5885	0.44	-	2.77	1.94
Informal Emp.	422	0.05	-	1.41	0.79	562	0.04	-	1.28	0.68
Self-Emp.	2775	0.30	-	2.99	2.73	3027	0.23	-	2.60	2.34
Non Part.	583	0.06	-	-	-	2167	0.16	-	-	-
$K \leq 5$						893	0.41			
$5 < K \leq 13$						516	0.24			

Note: Wage distributions are trimmed at the top and bottom 1 percentile by gender, education group and type of job, and are reported in US Dollars of December 2016 (Exchange Rate = 3009.86 Colombian Pesos/US). A worker is categorized as informal if he/she reports not having benefits of social security. K means proportion of women with the presence of kids in the household with respect to non participating women.

Table E.12: Colombia - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	0.0950	0.0216	0.7977	0.3285	0.9019	0.8454
	(0.0042)	(0.1220)	(0.0139)	(0.0414)	(0.0210)	(0.0253)
λ_F	0.0746	0.0379	0.1443	0.0757	0.0997	0.0875
	(0.0016)	(0.0146)	(0.0111)	(0.0059)	(0.0035)	(0.0028)
λ_S	0.1727	0.1439	0.4299	0.2744	0.1105	0.0833
	(0.0040)	(0.0335)	(0.1365)	(0.0323)	(0.0063)	(0.0022)
δ_F	0.0291	0.0392	0.0228	0.0457	0.0183	0.0240
	(0.0001)	(0.0156)	(0.0018)	(0.0041)	(0.0006)	(0.0008)
δ_S	0.0190	0.0284	0.0116	0.0158	0.0240	0.0374
	(0.0001)	(0.0066)	(0.0018)	(0.0018)	(0.0010)	(0.0007)
μ_F	1.1613	1.1684	1.0158	1.1223	1.7155	1.8122
	(0.0072)	(0.0277)	(0.0094)	(0.0091)	(0.0223)	(0.0118)
σ_F	0.2402	0.0045	0.0019	0.0006	0.6252	0.0167
	(0.0084)	(0.0070)	(0.0010)	(0.0007)	(0.0280)	(0.0053)
μ_I	0.7369	0.5950	-0.5970	0.5507	-1.3506	-1.3141
	(0.0109)	(0.0449)	(0.0383)	(0.0338)	(0.1015)	(0.1093)
σ_I	0.3455	0.0082	0.7279	0.2083	1.1012	1.0514
	(0.0107)	(0.0586)	(0.0356)	(0.1033)	(0.0676)	(0.0689)
μ_S	-0.0266	-0.3949	-1.1005	-2.5203	0.4301	0.5815
	(0.0083)	(0.0295)	(0.3177)	(0.2928)	(0.0717)	(0.0331)
σ_S	0.5487	0.6566	0.8905	1.6580	0.9237	0.7444
	(0.0055)	(0.0833)	(0.0752)	(0.1859)	(0.0357)	(0.0215)
σ_{ME}	0.1521	0.3836	0.3441	0.3379	0.4046	0.6196
	(0.0064)	(0.0733)	(0.0043)	(0.0318)	(0.0185)	(0.0042)
γ	27.1017	36.9147	3.8723	3.5150	3.0554	2.1419
γ_{k5}	-	34.5620	-	3.1040	-	1.8271
γ_{k13}	-	39.1202	-	3.8469	-	2.2715
γ_{other}	-	37.3036	-	3.6484	-	2.3540
b	-4.7300	-2.4144	-1.6264	-1.9234	-5.2874	-3.4863
c	0.1371	0.1371	0.1520	0.1520	0.2139	0.2139
$LogLikelihood$	-17037	-12564	-17264	-16544	-25763	-33577
N	9947	12060	8956	10581	9171	13252

Note: Bootstrap standard errors (based on 100 replications) in parenthesis. Non estimated parameters: $\beta = 0.5$, $\tau = 0.31$ and $\rho = 0.053$.

Table E.13: Colombia - Labor Market Dynamics and States

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
h_u									
Data	0.318	0.219	0.690	0.247	0.192	0.776	0.188	0.166	0.886
Model	0.322	0.220	0.683	0.247	0.206	0.834	0.188	0.166	0.886
$h_{u \to e_F}$									
Model	0.075	0.039	0.519	0.144	0.076	0.527	0.099	0.087	0.884
$h_{u \to e_I}$									
Model	0.075	0.039	0.519	0.033	0.076	2.325	0.009	0.008	0.912
$h_{u \to e_S}$									
Model	0.173	0.142	0.824	0.071	0.054	0.769	0.079	0.070	0.885
u									
Data	0.061	0.069	1.125	0.064	0.093	1.443	0.092	0.122	1.327
Model	0.066	0.125	1.899	0.068	0.129	1.913	0.098	0.145	1.486
e_F									
Data	0.179	0.055	0.309	0.408	0.212	0.520	0.496	0.444	0.895
Model	0.168	0.121	0.718	0.427	0.214	0.501	0.530	0.531	1.002
e_I									
Data	0.132	0.078	0.588	0.091	0.088	0.963	0.046	0.042	0.922
Model	0.168	0.121	0.718	0.097	0.214	2.210	0.049	0.051	1.034
e_S									
Data	0.552	0.348	0.631	0.390	0.291	0.747	0.303	0.228	0.755
Model	0.597	0.633	1.060	0.409	0.443	1.083	0.323	0.273	0.845
np									
Data	0.076	0.450	5.907	0.046	0.315	6.919	0.064	0.164	2.572
Model	0.076	0.450	5.907	0.046	0.315	6.919	0.064	0.164	2.572

Table E.14: Colombia - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	3.288	3.208	0.976	2.762	3.072	1.112	6.759	6.125	0.906
$SD(x_F)$									
Model	0.801	0.012	0.015	0.005	0.002	0.367	4.674	0.103	0.022
$E[x_I]$									
Model	2.218	1.807	0.815	0.717	1.773	2.473	0.475	0.467	0.983
$SD[x_I]$									
Model	0.790	0.014	0.017	0.601	0.373	0.621	0.730	0.664	0.910
$E[x_S]$									
Model	1.132	0.836	0.738	0.503	0.318	0.633	2.355	2.360	1.002
$SD[x_S]$									
Model	0.671	0.613	0.914	0.548	1.216	2.218	2.734	2.030	0.743
Y_W									
Model	1.716	1.298	0.756	2.042	1.821	0.892	5.204	4.778	0.918
Y_C									
Model	1.481	0.624	0.422	1.817	1.086	0.597	4.396	3.416	0.777
$E[w\|e_F]$									
Data	1.306	1.169	0.895	1.448	1.305	0.902	3.055	2.775	0.908
Model	1.300	1.243	0.956	1.458	1.347	0.924	3.049	2.767	0.907
$SD[w\|e_F]$									
Data	0.411	0.228	0.554	0.544	0.378	0.695	2.245	1.941	0.865
Model	0.371	0.481	1.294	0.519	0.471	0.908	2.337	1.899	0.812
$E[w\|e_I]$									
Data	1.082	0.870	0.804	1.127	0.976	0.866	1.411	1.282	0.908
Model	1.093	0.852	0.780	1.101	0.980	0.891	1.392	1.243	0.893
$SD[w\|e_I]$									
Data	0.386	0.359	0.928	0.407	0.352	0.866	0.793	0.683	0.861
Model	0.434	0.345	0.795	0.534	0.388	0.726	1.134	0.967	0.853
$E[w\|e_S]$									
Data	1.122	0.805	0.717	1.398	1.067	0.763	2.985	2.599	0.871
Model	1.130	0.849	0.751	1.398	1.235	0.884	3.055	2.699	0.883
$SD[w\|e_S$									
Data	0.658	0.572	0.870	0.912	0.845	0.926	2.734	2.338	0.855
Model	0.703	0.752	1.070	0.971	1.959	2.017	3.640	2.934	0.806

Note: $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, Y_W is the output per worker, Y_C is the output per capita, $E[w|e]$ is the average wage conditional on the employment status e, and finally $SD[w|e]$ is the standard deviation of wages conditioning in the employment status e.

Table E.15: Colombia - Policy Experiments

	Benchmark			Policy Exp. 1		Policy Exp. 2	
	M	W	W/M	W	W/M	W	W/M
Primary							
u	0.066	0.125	1.899	0.125	1.899	0.125	1.900
e_F	0.168	0.121	0.718	0.121	0.718	0.121	0.718
e_I	0.168	0.121	0.718	0.121	0.718	0.121	0.718
e_S	0.597	0.633	1.060	0.633	1.060	0.633	1.060
np	0.076	0.450	5.907	0.369	4.836	0.046	0.599
h_u	0.322	0.220	0.683	0.220	0.683	0.220	0.682
Y_W	1.716	1.298	0.756	1.298	0.756	1.428	0.832
Y_C	1.481	0.624	0.422	0.717	0.484	1.193	0.805
$E[w\|e_F]$	1.302	1.238	0.951	1.238	0.951	1.399	1.074
$E[w\|e_I]$	0.894	0.703	0.787	0.703	0.787	0.811	0.907
$E[w\|e_S]$	0.480	0.332	0.693	0.332	0.693	0.403	0.841
Res. W.	0.095	0.027	0.285	0.027	0.285	0.105	1.102
Secondary							
u	0.068	0.129	1.913	0.129	1.913	0.136	2.009
e_F	0.427	0.214	0.501	0.214	0.501	0.225	0.526
e_I	0.097	0.214	2.210	0.214	2.210	0.225	2.320
e_S	0.409	0.443	1.083	0.443	1.083	0.415	1.016
np	0.046	0.315	6.919	0.238	5.232	0.222	4.878
h_u	0.247	0.206	0.834	0.206	0.834	0.200	0.810
Y_W	2.042	1.821	0.892	1.821	0.892	2.080	1.019
Y_C	1.817	1.086	0.597	1.208	0.665	1.398	0.769
$E[w\|e_F]$	1.453	1.313	0.904	1.313	0.904	1.478	1.017
$E[w\|e_I]$	0.992	0.841	0.847	0.841	0.847	0.958	0.966
$E[w\|e_S]$	0.935	0.649	0.694	0.649	0.694	0.781	0.835
Res. W.	0.797	0.329	0.412	0.329	0.412	0.428	0.537
Tertiary							
u	0.098	0.145	1.486	0.145	1.486	0.147	1.506
e_F	0.530	0.531	1.002	0.531	1.002	0.538	1.015
e_I	0.049	0.051	1.034	0.051	1.034	0.043	0.863
e_S	0.323	0.273	0.845	0.273	0.845	0.272	0.843
np	0.064	0.164	2.572	0.111	1.738	0.103	1.628
h_u	0.188	0.166	0.886	0.166	0.886	0.164	0.872
Y_W	5.204	4.778	0.918	4.778	0.918	5.308	1.020
Y_C	4.396	3.416	0.777	3.632	0.826	4.058	0.923
$E[w\|e_F]$	3.046	2.760	0.906	2.760	0.906	3.101	1.018
$E[w\|e_I]$	1.257	1.166	0.927	1.166	0.927	1.365	1.086
$E[w\|e_S]$	1.619	1.448	0.894	1.448	0.894	1.664	1.028
Res. W.	0.902	0.845	0.937	0.845	0.937	1.059	1.174

Table E.15: Colombia - Policy Experiments – continued from previous page

	Policy Exp. 3		Policy Exp. 4 ($\tau = 0$)		Policy Exp. 4 ($c = 0$)	
	W	W/M	W	W/M	W	W/M
Primary						
u	0.125	1.899	0.125	1.899	0.125	1.899
e_F	0.121	0.718	0.121	0.718	0.121	0.718
e_I	0.121	0.718	0.121	0.718	0.121	0.718
e_S	0.633	1.060	0.633	1.060	0.633	1.060
np	0.448	5.879	0.443	6.322	0.347	6.656
h_u	0.220	0.683	0.220	0.683	0.220	0.683
Y_W	1.298	0.756	1.298	0.756	1.298	0.756
Y_C	0.627	0.423	0.633	0.424	0.742	0.488
$E[w\|e_F]$	1.332	1.023	1.618	0.956	1.242	0.949
$E[w\|e_I]$	0.756	0.846	0.917	0.792	0.708	0.785
$E[w\|e_S]$	0.357	0.744	0.432	0.702	0.337	0.692
Res. W.	0.027	0.286	0.028	0.281	0.036	0.329
Secondary						
u	0.130	1.923	0.131	1.808	0.132	2.003
e_F	0.215	0.504	0.218	0.474	0.219	0.525
e_I	0.215	2.221	0.218	2.404	0.219	1.756
e_S	0.440	1.077	0.434	1.149	0.429	1.097
np	0.310	6.811	0.299	8.735	0.292	6.672
h_u	0.205	0.831	0.204	0.876	0.203	0.794
Y_W	1.829	0.896	1.850	0.865	1.863	0.924
Y_C	1.098	0.604	1.127	0.588	1.145	0.636
$E[w\|e_F]$	1.403	0.966	1.677	0.923	1.324	0.908
$E[w\|e_I]$	0.895	0.902	1.058	0.842	0.852	0.911
$E[w\|e_S]$	0.693	0.741	0.825	0.696	0.680	0.719
Res. W.	0.333	0.418	0.344	0.395	0.350	0.434
Tertiary						
u	0.146	1.491	0.147	1.482	0.142	1.481
e_F	0.533	1.005	0.537	0.995	0.520	0.999
e_I	0.050	1.009	0.047	1.034	0.071	1.062
e_S	0.272	0.841	0.269	0.852	0.267	0.843
np	0.157	2.476	0.143	2.790	0.162	2.585
h_u	0.165	0.881	0.163	0.888	0.169	0.888
Y_W	4.794	0.921	4.835	0.916	4.687	0.915
Y_C	3.450	0.785	3.533	0.784	3.370	0.776
$E[w\|e_F]$	2.948	0.968	3.516	0.908	2.763	0.906
$E[w\|e_I]$	1.241	0.987	1.471	0.923	1.055	0.923
$E[w\|e_S]$	1.542	0.952	1.824	0.886	1.453	0.894
Res. W.	0.863	0.957	0.908	0.934	0.851	0.938

Table E.16: Mexico - Descriptive Statistics

Labor Market	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w
States	Men					Women				
Education Group: Primary										
Unemployed	328	0.03	1.24	-	-	182	0.01	1.50	-	-
Formal Emp.	2412	0.24	-	1.42	0.59	1063	0.07	-	1.14	0.44
Informal Emp.	3480	0.35	-	1.22	0.52	1177	0.08	-	1.04	0.63
Self-Emp.	2415	0.24	-	1.67	1.14	2248	0.15	-	1.18	1.04
Non Part.	1413	0.14	-	-	-	10430	0.69	-	-	-
$K \leq 5$						3727	0.36			
$5 < K \leq 13$						2902	0.28			
Education Group: Secondary										
Unemployed	1076	0.04	1.95	-	-	713	0.02	1.87	-	-
Formal Emp.	11929	0.46	-	1.59	0.75	6235	0.19	-	1.39	0.69
Informal Emp.	6401	0.25	-	1.29	0.66	2991	0.09	-	1.15	0.67
Self-Emp.	4770	0.18	-	1.99	1.58	4001	0.12	-	1.67	1.63
Non Part.	1832	0.07	-	-	-	18215	0.57	-	-	-
$K \leq 5$						7809	0.43			
$5 < K \leq 13$						5532	0.30			
Education Group: Tertiary										
Unemployed	782	0.06	2.73	-	-	647	0.04	2.61	-	-
Formal Emp.	7078	0.57	-	3.02	1.85	7227	0.42	-	2.86	1.63
Informal Emp.	1389	0.11	-	2.09	1.57	1380	0.08	-	2.02	1.48
Self-Emp.	1897	0.15	-	3.17	2.90	1474	0.09	-	2.64	2.62
Non Part.	1239	0.10	-	-	-	6358	0.37	-	-	-
$K \leq 5$						2115	0.33			
$5 < K \leq 13$						1545	0.24			

Note: Wage distributions are trimmed at the top and bottom 1 percentile by gender, education group and type of job, and are reported in US Dollars of December 2016 (Exchange Rate = 20.52 Mexican Pesos/US). A worker is categorized as informal if he/she reports not having access to health care. K means proportion of women with the presence of kids in the household with respect to non participating women.

Table E.17: Mexico - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	0.0769	0.0866	0.9945	0.6806	1.4058	1.1647
	(0.0316)	(0.0068)	(0.0149)	(0.0092)	(0.0572)	(0.0267)
λ_F	0.2605	0.1790	0.2613	0.2914	0.2164	0.2748
	(0.0162)	(0.0161)	(0.0128)	(0.0177)	(0.0116)	(0.0172)
λ_S	0.2825	0.3073	0.3035	0.5869	0.1752	0.4198
	(0.0120)	(0.0233)	(0.0415)	(0.0893)	(0.0160)	(0.1428)
δ_F	0.0290	0.0291	0.0236	0.0336	0.0239	0.0246
	(0.0018)	(0.0026)	(0.0012)	(0.0020)	(0.0013)	(0.0015)
δ_S	0.0384	0.0248	0.0248	0.0179	0.0443	0.0243
	(0.0016)	(0.0019)	(0.0023)	(0.0026)	(0.0035)	(0.0066)
μ_F	1.2965	1.0563	1.0639	1.0282	1.8190	1.8075
	(0.0200)	(0.0286)	(0.0087)	(0.0086)	(0.0122)	(0.0092)
σ_F	0.1133	0.1178	0.0036	0.0190	0.0138	0.0228
	(0.1065)	(0.1153)	(0.0013)	(0.0041)	(0.1028)	(0.0093)
μ_I	0.9051	0.6911	0.1909	-0.1791	-0.3006	-0.6903
	(0.0149)	(0.0275)	(0.0109)	(0.0102)	(0.0930)	(0.0502)
σ_I	0.1614	0.3504	0.4402	0.7646	0.9142	1.1595
	(0.0824)	(0.0569)	(0.0229)	(0.0185)	(0.0698)	(0.0409)
μ_S	0.3910	-0.1133	-0.3025	-1.6260	0.5568	-1.2779
	(0.0286)	(0.0350)	(0.1823)	(0.2935)	(0.1360)	(0.5792)
σ_S	0.5207	0.7612	0.8393	1.3077	0.7454	1.2796
	(0.0463)	(0.0386)	(0.0541)	(0.0748)	(0.0620)	(0.1307)
σ_{ME}	0.3720	0.3206	0.4321	0.4432	0.5736	0.5552
	(0.1398)	(0.1523)	(0.0025)	(0.0040)	(0.0151)	(0.0042)
γ	25.5112	4.2740	2.6677	0.8351	1.6376	0.8487
γ_{k5}	-	3.7243	-	0.6902	-	0.7739
γ_{k13}	-	4.6410	-	0.8890	-	0.8623
γ_{other}	-	4.5131	-	0.9857	-	0.8958
b	-13.7364	-9.0289	-3.4647	-4.5475	-6.6889	-8.2235
c	0.1495	0.1495	0.1669	0.1669	0.2116	0.2116
$Likelihood$	-18023	-9219	-53030	-30738	-31751	-28936
$LRTest$	194.6602	5.8042	184.2963	644.9959	0.0004	76.1075
N	10048	15100	26008	32155	12385	17086

Note: Bootstrap standard errors (based on 100 replications) in parenthesis. Non estimated parameters: $\beta = 0.5$, $\tau = 0.33$ and $\rho = 0.056$.

Table E.18: Mexico - Labor Market Dynamics and States

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
h_u									
Data	0.804	0.665	0.827	0.512	0.535	1.047	0.366	0.383	1.045
Model	0.804	0.665	0.827	0.512	0.536	1.048	0.366	0.383	1.045
$h_{u \to e_F}$									
Model	0.261	0.179	0.687	0.261	0.284	1.089	0.216	0.275	1.271
$h_{u \to e_I}$									
Model	0.261	0.179	0.687	0.140	0.140	0.999	0.042	0.053	1.242
$h_{u \to e_S}$									
Model	0.283	0.307	1.086	0.111	0.112	1.011	0.108	0.055	0.513
u									
Data	0.033	0.012	0.369	0.041	0.022	0.536	0.063	0.038	0.600
Model	0.038	0.039	1.026	0.045	0.051	1.149	0.070	0.060	0.860
e_F									
Data	0.240	0.070	0.293	0.459	0.194	0.423	0.571	0.423	0.740
Model	0.341	0.240	0.703	0.493	0.443	0.899	0.635	0.673	1.060
e_I									
Data	0.346	0.078	0.225	0.246	0.093	0.378	0.112	0.081	0.720
Model	0.341	0.240	0.703	0.265	0.219	0.825	0.125	0.129	1.036
e_S									
Data	0.240	0.149	0.619	0.183	0.124	0.678	0.153	0.086	0.563
Model	0.280	0.481	1.721	0.197	0.287	1.455	0.170	0.137	0.807
np									
Data	0.141	0.691	4.912	0.070	0.566	8.042	0.100	0.372	3.720
Model	0.141	0.691	4.912	0.070	0.566	8.042	0.100	0.372	3.720

Table E.19: Mexico - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	3.680	2.896	0.787	2.898	2.798	0.966	6.166	6.097	0.989
$SD(x_F)$									
Model	0.417	0.342	0.821	0.009	0.006	0.657	0.037	0.139	3.701
$E[x_I]$									
Model	2.505	2.122	0.847	1.333	1.120	0.840	1.125	0.982	0.873
$SD[x_I]$									
Model	0.406	0.767	1.888	0.617	1.003	1.626	1.285	1.654	1.287
$E[x_S]$									
Model	1.693	1.193	0.705	1.052	0.506	0.481	2.306	0.631	0.274
$SD[x_S]$									
Model	0.945	1.057	1.119	1.063	1.019	0.959	1.985	1.285	0.647
Y_W									
Model	2.686	1.850	0.689	2.391	2.234	0.934	5.196	5.194	1.000
Y_C									
Model	2.220	0.550	0.248	2.124	0.919	0.433	4.348	3.065	0.705
$E[w\|e_F]$									
Data	1.424	1.136	0.798	1.589	1.389	0.874	3.022	2.859	0.946
Model	1.430	1.138	0.796	1.594	1.385	0.869	3.046	2.895	0.950
$SD[w\|e_F]$									
Data	0.588	0.437	0.744	0.748	0.690	0.922	1.852	1.630	0.881
Model	0.576	0.404	0.701	0.723	0.644	0.891	1.922	1.736	0.903
$E[w\|e_I]$									
Data	1.216	1.040	0.855	1.288	1.148	0.891	2.091	2.020	0.966
Model	1.226	1.030	0.840	1.295	1.140	0.880	2.085	2.008	0.963
$SD[w\|e_I]$									
Data	0.517	0.628	1.216	0.663	0.672	1.013	1.574	1.483	0.942
Model	0.526	0.538	1.024	0.668	0.833	1.246	1.734	1.926	1.111
$E[w\|e_S]$									
Data	1.672	1.175	0.703	1.988	1.674	0.842	3.171	2.636	0.831
Model	1.688	1.189	0.705	1.963	1.735	0.884	3.133	2.655	0.847
$SD[w\|e_S$									
Data	1.137	1.039	0.914	1.575	1.634	1.037	2.902	2.620	0.903
Model	1.226	1.208	0.985	1.612	1.949	1.209	3.013	2.989	0.992

Note: $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, Y_W is the output per worker, Y_C is the output per capita, $E[w|e]$ is the average wage conditional on the employment status e, and finally $SD[w|e]$ is the standard deviation of wages conditioning in the employment status e.

Table E.20: Mexico - Policy Experiments

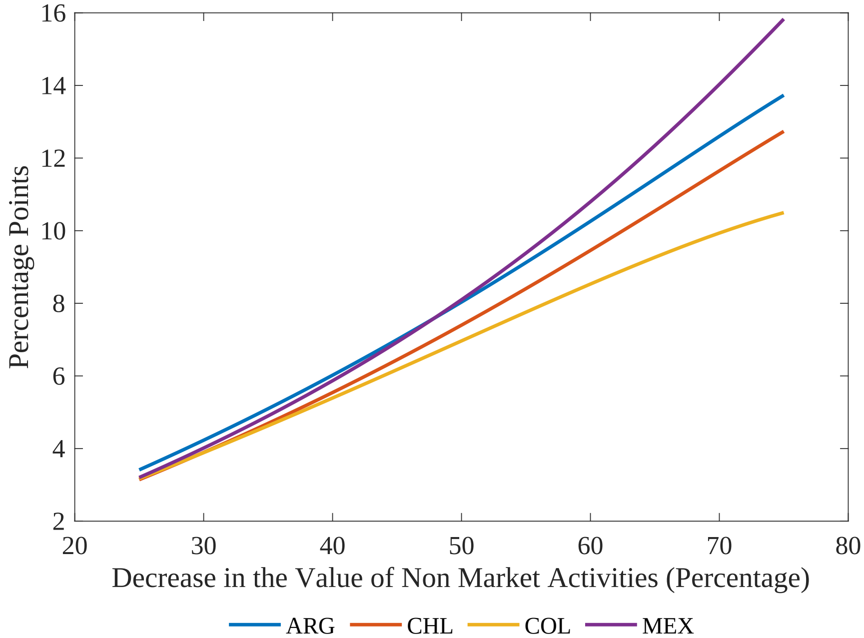
	Benchmark			Policy Exp. 1		Policy Exp. 2	
	M	W	W/M	W	W/M	W	W/M
Primary							
u	0.038	0.039	1.026	0.039	1.026	0.039	1.033
e_F	0.341	0.240	0.703	0.240	0.703	0.242	0.708
e_I	0.341	0.240	0.703	0.240	0.703	0.242	0.708
e_S	0.280	0.481	1.721	0.481	1.721	0.478	1.708
np	0.141	0.691	4.912	0.623	4.428	0.387	2.750
h_u	0.804	0.665	0.827	0.665	0.827	0.661	0.822
Y_W	2.686	1.850	0.689	1.850	0.689	2.049	0.763
Y_C	2.220	0.550	0.248	0.671	0.302	1.207	0.544
$E[w\|e_F]$	1.422	1.132	0.796	1.132	0.796	1.309	0.920
$E[w\|e_I]$	0.980	0.841	0.858	0.841	0.858	0.989	1.009
$E[w\|e_S]$	0.675	0.492	0.729	0.492	0.729	0.611	0.906
Res. W.	0.077	0.087	1.129	0.087	1.129	0.222	2.900
Secondary							
u	0.045	0.051	1.149	0.051	1.149	0.052	1.175
e_F	0.493	0.443	0.899	0.443	0.899	0.453	0.920
e_I	0.265	0.219	0.825	0.219	0.825	0.221	0.833
e_S	0.197	0.287	1.455	0.287	1.455	0.273	1.385
np	0.070	0.566	8.042	0.475	6.750	0.507	7.197
h_u	0.512	0.536	1.048	0.536	1.048	0.526	1.029
Y_W	2.391	2.234	0.934	2.234	0.934	2.467	1.032
Y_C	2.124	0.919	0.433	1.112	0.523	1.153	0.543
$E[w\|e_F]$	1.587	1.391	0.877	1.391	0.877	1.563	0.985
$E[w\|e_I]$	1.153	1.000	0.867	1.000	0.867	1.121	0.972
$E[w\|e_S]$	1.247	0.988	0.792	0.988	0.792	1.124	0.902
Res. W.	0.994	0.679	0.683	0.679	0.683	0.812	0.816
Tertiary							
u	0.070	0.060	0.860	0.060	0.860	0.062	0.888
e_F	0.635	0.673	1.060	0.673	1.060	0.695	1.095
e_I	0.125	0.129	1.036	0.129	1.036	0.121	0.969
e_S	0.170	0.137	0.807	0.137	0.807	0.122	0.714
np	0.100	0.372	3.720	0.299	2.985	0.293	2.928
h_u	0.366	0.383	1.045	0.383	1.045	0.370	1.010
Y_W	5.196	5.194	1.000	5.194	1.000	5.826	1.121
Y_C	4.348	3.065	0.705	3.424	0.787	3.863	0.888
$E[w\|e_F]$	3.021	2.874	0.951	2.874	0.951	3.245	1.074
$E[w\|e_I]$	1.831	1.763	0.963	1.763	0.963	2.040	1.114
$E[w\|e_S]$	1.901	1.599	0.841	1.599	0.841	1.888	0.993
Res. W.	1.406	1.165	0.828	1.165	0.828	1.447	1.029

Table E.20: Mexico - Policy Experiments – continued from previous page

	Policy Exp. 3		Policy Exp. 4 ($\tau = 0$)		Policy Exp. 4 ($c = 0$)	
	W	W/M	W	W/M	W	W/M
			Primary			
u	0.039	1.026	0.039	1.026	0.039	1.027
e_F	0.240	0.703	0.240	0.703	0.240	0.704
e_I	0.240	0.703	0.240	0.703	0.240	0.704
e_S	0.481	1.721	0.481	1.721	0.481	1.720
np	0.687	4.885	0.678	5.549	0.630	9.717
h_u	0.665	0.827	0.665	0.827	0.665	0.827
Y_W	1.851	0.689	1.851	0.689	1.852	0.690
Y_C	0.557	0.251	0.573	0.253	0.659	0.273
$E[w\|e_F]$	1.220	0.858	1.493	0.794	1.143	0.795
$E[w\|e_I]$	0.906	0.924	1.107	0.856	0.852	0.856
$E[w\|e_S]$	0.529	0.784	0.643	0.724	0.504	0.730
Res. W.	0.088	1.146	0.091	1.107	0.108	1.013
			Secondary			
u	0.052	1.166	0.054	1.130	0.050	1.169
e_F	0.450	0.913	0.468	0.884	0.431	0.914
e_I	0.216	0.816	0.210	0.877	0.253	0.828
e_S	0.282	1.428	0.268	1.459	0.267	1.471
np	0.557	7.904	0.532	10.229	0.554	8.510
h_u	0.529	1.033	0.511	1.075	0.558	1.040
Y_W	2.258	0.944	2.318	0.933	2.191	0.940
Y_C	0.949	0.447	1.027	0.458	0.928	0.445
$E[w\|e_F]$	1.486	0.937	1.776	0.887	1.405	0.877
$E[w\|e_I]$	1.073	0.930	1.299	0.880	0.954	0.847
$E[w\|e_S]$	1.065	0.854	1.304	0.804	1.018	0.798
Res. W.	0.700	0.704	0.755	0.681	0.705	0.689
			Tertiary			
u	0.061	0.870	0.063	0.865	0.059	0.861
e_F	0.681	1.073	0.703	1.067	0.658	1.062
e_I	0.125	1.005	0.115	1.050	0.151	1.025
e_S	0.132	0.776	0.119	0.748	0.132	0.801
np	0.357	3.571	0.319	4.242	0.367	3.755
h_u	0.378	1.031	0.366	1.047	0.392	1.047
Y_W	5.246	1.010	5.375	1.007	5.102	1.000
Y_C	3.166	0.728	3.428	0.749	3.041	0.709
$E[w\|e_F]$	3.083	1.020	3.721	0.961	2.883	0.952
$E[w\|e_I]$	1.912	1.045	2.383	0.992	1.656	0.952
$E[w\|e_S]$	1.738	0.914	2.175	0.878	1.619	0.846
Res. W.	1.213	0.863	1.345	0.852	1.182	0.832

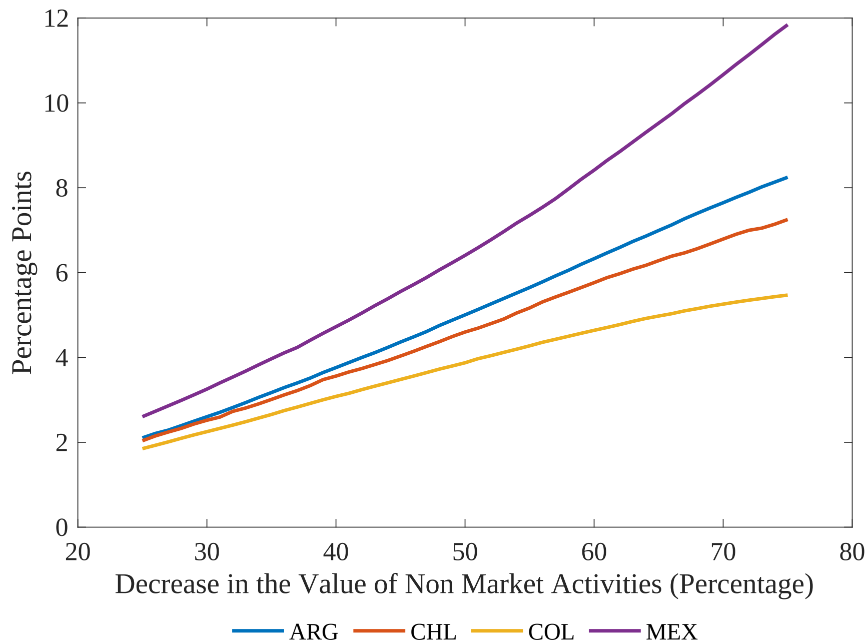
F Additional Material on Policy Experiments

Figure F.1: Child-care Provision Policy: Impact on Female Participation Rates



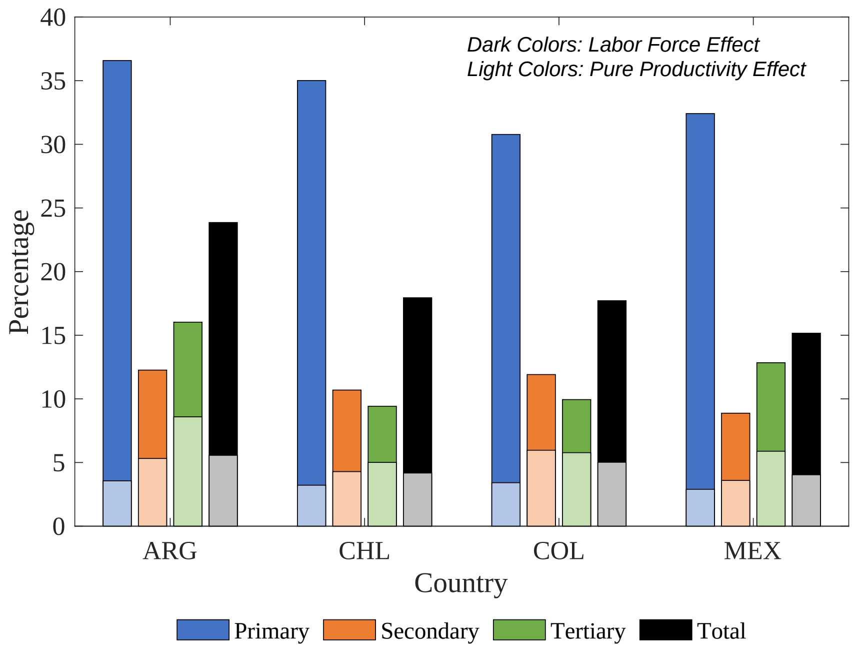
NOTE: Figure reports percentage points changes in female participation rates as a result of *policy experiment 1*: A range between 25% and 75% of reductions in the average value of non-participation for mother with children aged 5 or younger. See Section 6 for more details.

Figure F.2: Child-care Provision Policy: Impact on Output per Capita



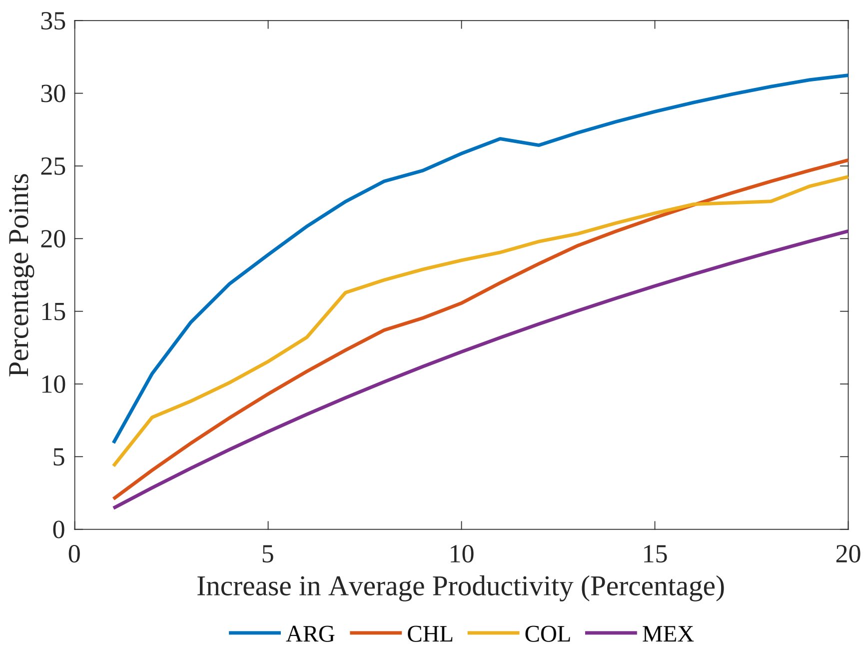
NOTE: Figure reports percentage points changes in output as a result of *policy experiment 1*: A range between 25% and 75% of reductions in the average value of non-participation for mother with children aged 5 or younger is considered. See Section 6 for more details.

Figure F.3: Increase Female Productivity Policy: Impact on Output per Capita by Channel



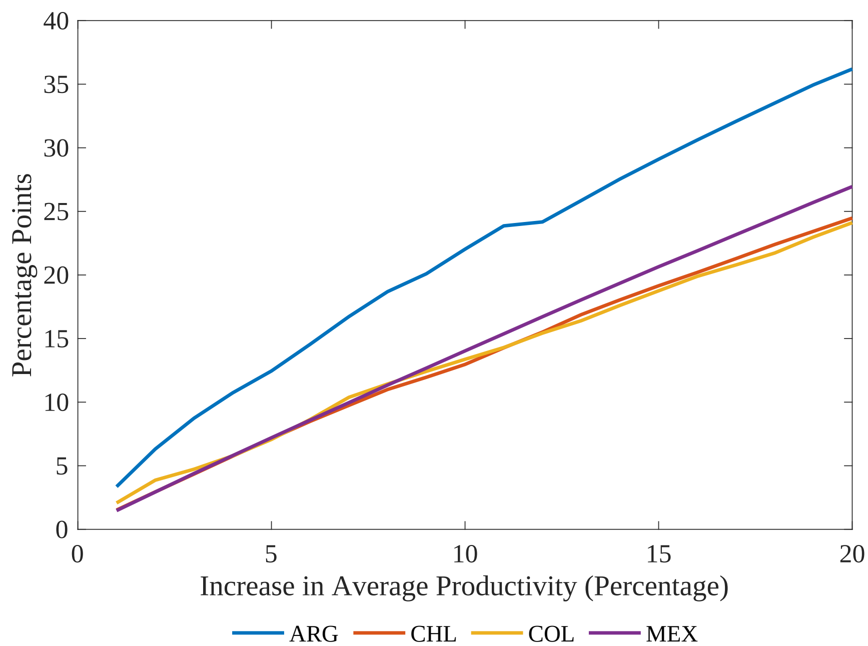
NOTE: Figure reports percentage points changes in output as a result of *policy experiment 2*: increasing the average productivity of women by 10%. See Section 6 for more details. The overall increase is decomposed in the portion due to the 10% productivity increase (Pure Productivity Effects) and the portion due to the increase in participation resulting from the productivity increase (Labor Force Effect).

Figure F.4: Increase Female Productivity Policy: Impact on Female Participation Rates



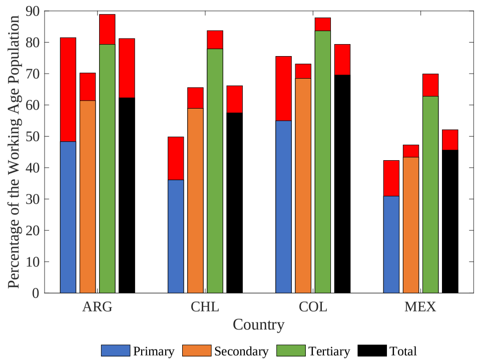
Note: Figure reports percentage points changes in participation rates as a result of *policy experiment 2*: A range between 1% and 20% increasing the average productivity of women is considered. See Section 6 for more details.

Figure F.5: Increase Female Productivity Policy: Impact on Output per Capita

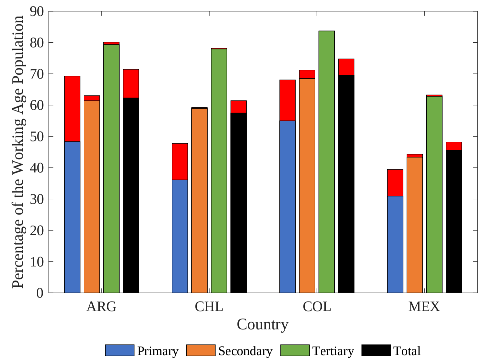


Note: Figure reports percentage points changes in output as a result of *policy experiment 2*: A range between 1% and 20% increasing the average productivity of women is considered. See Section 6 for more details.

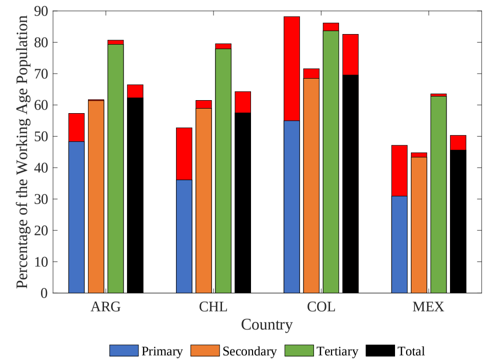
Figure F.6: Policy 5: Increase Female Productivity by Sector Policy



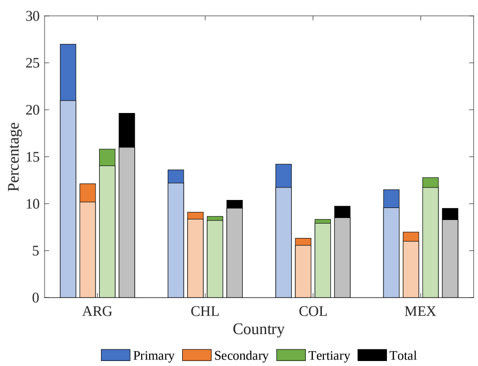
(a) Impact on Female Part. Rates (Formal)



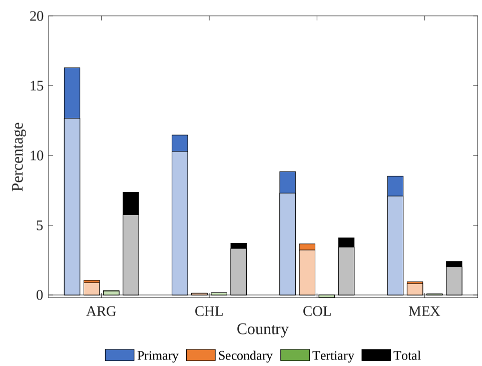
(b) Impact on Female Part. Rates (Informal)



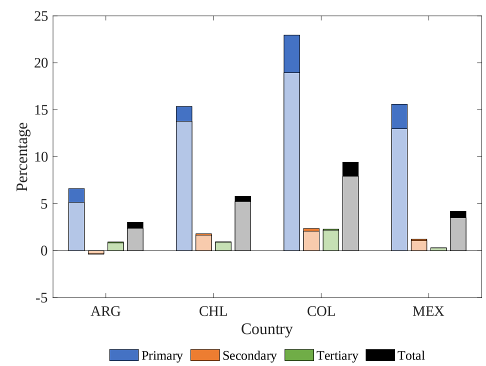
(c) Impact on Female Part. Rates (Self-Emp.)



(d) Impact on Output per Capita (Formal)



(e) Impact on Output per Capita (Informal)



(f) Impact on Output per Capita (Self-Emp.)

NOTE: The policy reported in panels (a) and (d) increases women average productivity by 10% in the formal sector; the one in panels (b) and (e) increases women average productivity by 10% in the informal sector; the one in panels (c) and (f) increases women average productivity by 10% for self-employed. In panels (a), (b) and (c) the overall length of the column is the post-policy participation rate. The red darker segment is the impact of the policy. In panels (d), (e) and (f) we report the percentage points changes in output per capita as a result of the policy. Light colored bars represent the effect on output taking into account differences in average weekly hours worked by men and women. See Section 6 for more details.

G Robustness Analysis

This section of the appendix provides robustness checks. The first concerns the distributional assumption on the value of non participation distribution $Q_i(z)$; the second the Nash-bargaining weight β; and the third the mobility rates λ and δ.

The first robustness check is reported in Figure G.1. Since the empirical identification of the value of non participation distribution $Q_i(z)$ is quite limited – we can only use one moment: the proportion of agents non-participating – we assess the importance of the specific distributional assumption we make. We evaluate importance by re-estimating the model under different distributional assumptions and then re-running the relevant policy experiments. In this case, the most relevant experiment is *policy experiment 1* where we reduce in half the average value of non-participation for mother with children aged 5 or younger. It is the most relevant because the policy directly affect non-participation values. We are constrained in the alternative distributional assumptions we can make. First, we can identify and estimate only one parameter. Second, the distribution should be on a positive support. We have chosen to use a lognormal distribution since it satisfies the support condition. In order to make it a one-parameter distribution, we fix the shape parameter σ and estimate only the location parameter. We fix σ at two values: 1 and 0.5.

The original result under the exponential distribution assumption (ED) is in Panel (a). The results under the alternative lognormal distribution assumption (LND) are in Panel (b) and (c). The overall length of the column is the post-policy participation rate and the red darker segment is the impact of the policy. See Section 6 for more details. The results under the alternative distributional assumptions are qualitatively similar to benchmark: same direction of the impact, same ranking of magnitudes between schooling levels, same ranking across countries.

The second robustness check we perform refers to the Nash-bargaining weight β. In the paper, we impose symmetric bargaining for both men and women, fixing the parameter at 0.5. We are forced to do this because we do not have enough data information to identify it, a common problem in the literature (Flinn, 2006; Flabbi, 2010a). Still, the assumption may be more restrictive in our context because it does also imply that men and women share the same parameter. There are a number of reasons why that may not be the case. Some contributions have used this parameter as a proxy for possible discrimination, even if the empirical evidence is mixed (Eckstein and Wolpin, 1999; Bartolucci, 2013). Others have suggested that women and men are systematically different in their bargaining process (Castillo et al., 2013), something that could be captured by the parameter. In general, it could be an additional structural parameter over which men and women could differ, just as we currently allow for differences in productivity and mobility rates.

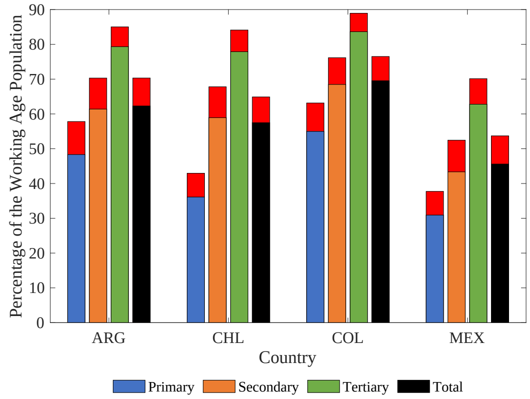
We check robustness with respect to the restriction by focusing on the policy where its impact should be largest: *Policy Experiment 2* where we increase the average productivity of women in the three sectors by 10%. Results of the exercise are reported in Figure G.2. Once again, changes in the parameters deliver result qualitatively similar to benchmark. Primary sees the strongest impact, impact that becomes slightly larger when women have more bargaining power. Across countries, Argentina experience the largest overall impact, the extent of which is almost unaffected by the different parameter combinations. The only country and schooling level where we see important differences is Colombia in the Primary school level: in this case, the impact on primary is significantly reduced when women have a high bargaining power ($\beta_W = 0.6$).

The third robustness exercise concerns the restriction that the arrival and termination rates for formal and informal employees are the same. As we discuss in Section 4.2, we have to impose $\lambda_F = \lambda_I$ and $\delta_F = \delta_I$ not because the theoretical identification cannot be attained but because the empirical identification is very weak for a number of country-education-gender groups. For a significant number of estimation samples we do not have enough data variation to obtain convergence of the likelihood function in the feasible parameters space.

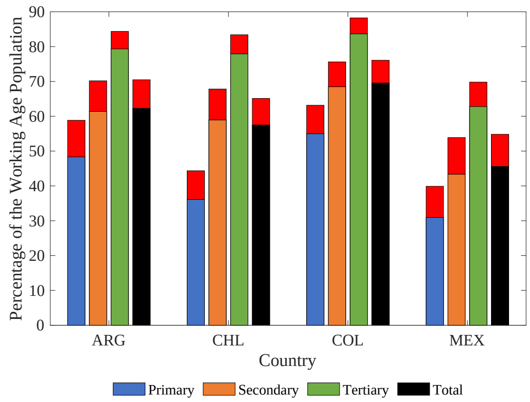
In this robustness section we report results for the one country on which it is possible to attain empirical identification on all estimation samples: Argentina. For Argentina, we estimate the model with and without the restriction. The model with the restriction is the benchmark we estimate in the paper and the model without the restriction allows both the arrival rate λ and the termination rate δ to be different for formals and informals. We use the estimation results to perform a specification test. Since the specification of the model with the restriction is nested in the one of the model without the restriction, it is straightforward to perform Likelihood Ratio tests where the null is the restricted model and the alternative is the unrestricted model. Table G.1 reports statistics and P-values of the test. The restriction is rejected only on one sample out of six: men with Secondary education. Even in this case, the differences in point estimates are not very large.[32]

[32]The arrival rate for formal is 0.1741 and for informal is 0.1106; the termination rate for formal is 0.0154 and for informal 0.0298.

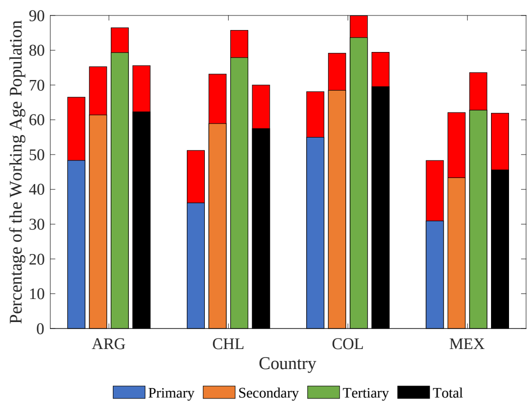
Figure G.1: Robustness Check 1: Child-care Provision Policy using Different Distributional Assumptions for the Value of Non Participation Distribution $Q_i(z)$



(a) Female Participation Rates (ED)



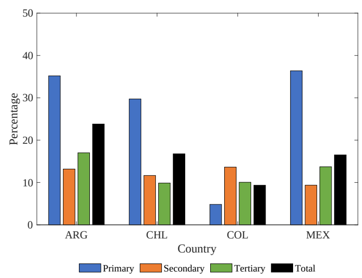
(b) Female Participation Rates (LND $\sigma = 1$)



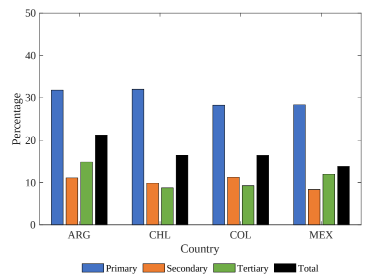
(c) Female Participation Rates (LND $\sigma = 0.5$)

NOTE: The figures report *policy experiment 1* under different parametric assumptions for the $Q_i(z)$ distribution. For each assumption, we re-estimate the model and re-run the experiments. The original result under the exponential distribution assumption (ED) is in Panel (a). The results under the alternative lognormal distribution assumption (LND) are in Panel (b) and (c). As in Figure F.1, the overall length of the column is the post-policy participation rate and the red darker segment is the impact of the policy. See Section 6 for more details.

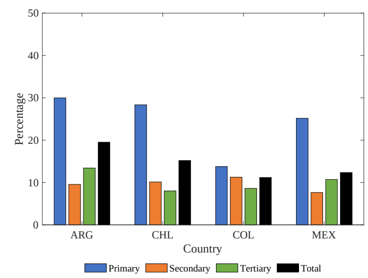
Figure G.2: Robustness Check 2: Increase in Female Productivity Policy using Different Nash Bargaining Coefficients β_W, β_M



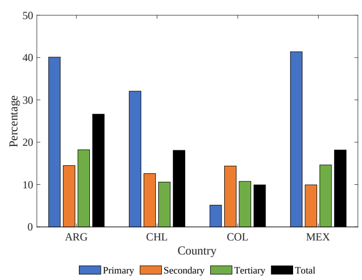
(a) $\beta_M = 0.4, \beta_W = 0.4$



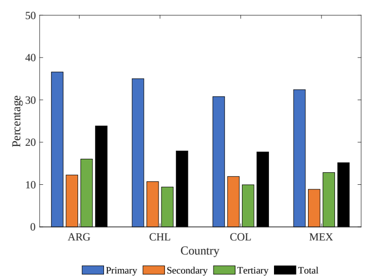
(b) $\beta_M = 0.4, \beta_W = 0.5$



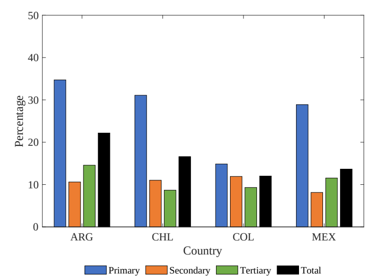
(c) $\beta_M = 0.4, \beta_W = 0.6$



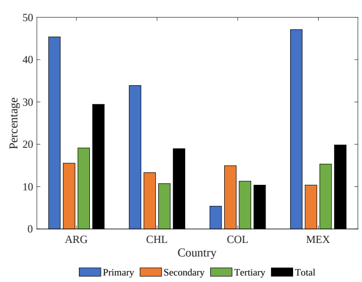
(d) $\beta_M = 0.5, \beta_W = 0.4$



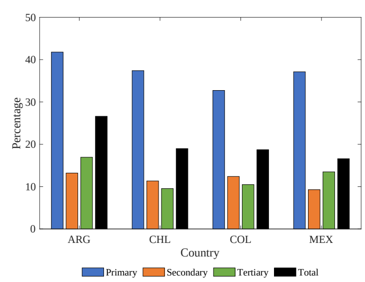
(e) $\beta_M = 0.5, \beta_W = 0.5$



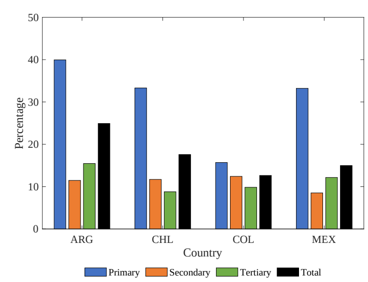
(f) $\beta_M = 0.5, \beta_W = 0.6$



(g) $\beta_M = 0.6, \beta_W = 0.4$



(h) $\beta_M = 0.6, \beta_W = 0.5$



(i) $\beta_M = 0.6, \beta_W = 0.6$

NOTE: The figures report *policy experiment 2* under different values combinations of nash-bargaining coefficients β_W, β_M. For each combination, we re-run the experiments. The original result under symmetric bargaining is reported in Panel (e). All panels report the percentage points changes in output as a result of the policy. As in Figure F.5, we report the effect on output taking into account differences in average weekly hours worked by men and women. See Section 6 for more details.

Table G.1: Likelihood Ratio Test for the restriction $\lambda_F = \lambda_I$ and $\delta_F = \delta_I$

	Argentina			
	Men		Women	
	Test Statistic	P-Value	Test Statistic	P-Value
Primary	0.0015	0.9993	0.0000	1.0000
Secondary	15.8573	0.0004	0.0000	1.0000
Tertiary	0.0384	0.9810	0.8226	0.6628

Note: The Table reports test statistics and P-values of the joint test with: $H_0 : \{\lambda_F = \lambda_I, \delta_F = \delta_I\}$