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Female Labor Force Participation, Labor Market Dynamic, and Growth*

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Abstract

The labor force participation of women is lower than the labor force participation of men. This empirical regularity is particularly acute in Latin America and the Caribbean (LAC). In terms of labor market productivity and growth potential, these lower participation rates constitute a reserve of untapped resources. Providing an estimate of the impact that increased female participation in the labor force has on labor market outcomes and GDP is therefore crucial but challenging. Two issues are of importance: sample selection and equilibrium effects. We develop a labor market model that is able to address these issues. We estimate the model on the microdata of five LAC countries. We find that both a childcare policy and a policy increasing women's productivity generate a positive impact on female participation and significant increases in GDP per capita. Our results suggest that relatively modest policies that are able to increase the participation of women in the labor market can provide a significant increase in GDP. However, we are not able to take into account the fiscal costs necessary to implement the policies or the possible negative externalities on household production.

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1 Introduction

1.1 Motivation

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 holds true particularly in Latin America and the Caribbean (LAC). For example, Busso and Fonseca (2015) showed that the average rate for female participation in LAC labor forces in 2010 was about 65% compared to about 76% in the United States. There are important differences between LAC countries, with values ranging from 50% in Honduras and Mexico to 70% in Peru and Uruguay.

In terms of labor market productivity and growth potential, these lower participation rates constitute a reserve of untapped resources. If these resources could be brought to the market, the production generated by the increased labor force is likely to have substantial positive impacts on the GDP. The potential positive impact of bringing more women to the labor market has increased over time as women continue to acquire more human capital with each passing generation. For example, schooling completed among women is now higher than men in all high-income economies and in many LAC economies. Argentina, Brazil, Colombia, and Uruguay all report a positive gender gap in years of schooling completed; that is, 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 in contrast to women having half a year less than men—a negative gap—in 1992.[2]

The objective of this paper is to provide estimates of changes in GDP implied by policies that increase the labor force participation of women on five LAC countries: Argentina, Chile, Colombia, Mexico, and Peru.

[1]See, for example, Blau and Kahn (2013), who show a gender difference in employment rates in a large sample of high-income countries, or Olivetti and Petrongolo (2008), who show a 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] See Marchionni (2015) for more details. The aggregate result is strongly driven by younger generations: The 25-34 age group shows a strong positive gap in favor of women; 35-44, a small positive gap; and 45-54, a strong negative gap. All data refer to 2012.

1.2 Challenges

Estimating the impact of an increase in female labor force participation on labor market outcomes and GDP is challenging. Two issues are of importance when considering such a counterfactual exercise:

1. sample selection and
2. equilibrium effects.

Sample selection refers to the difference in the type of individuals who are participating in the labor market with respect to those who are not. When we observe men and women who are currently producing labor in the market, earning wages, and contributing some level of productivity to the country's economy, we have to consider that a large proportion of women do not work. Therefore, the women who are currently working may differ from those who would enter the labor force as a result of policies designed to increase female labor force participation. For example, if the women who are currently working are more productive than those who are not, we could overestimate the impact of increasing female labor force participation. The opposite would be true if the women currently working are less productive that those who are not.

Equilibrium effect refers to the change in equilibrium prices and quantities that may result from a change in the labor market environment. The wage distribution and employment proportion observed in a given moment in an economy are the result of the meeting of labor demand and labor supply in the market. Wages and earnings are the prices realized as a result of this meeting; they may be called equilibrium prices. A significant increase in female labor supply implies a large increase in the amount of labor offered in the market. As a result of an increase in supply, wages and earnings will change. This is the first consequence, labeled here as a short-run equilibrium effect. Eventually, labor demand will also adjust because firms may decide to change their production mix and post more or fewer jobs at various skill levels. This demand-side behavior has the potential to change wages and earnings. This is the second consequence, and it is categorized as a long-run equilibrium effect. Both effects make it challenging to quantitatively evaluate the impact of an increase in female labor market participation by only observing wages and earnings before the increase is taking place. This is due to the fact that the observed data are extracted from an equilibrium that is different than the one realized after the increase in participation is taking place.

1.3 Approach

A possible approach that is able to take sample selection and equilibrium effects into account consists of specifying an economic model in which the channels generate the effects. Microlevel data for each specific country can then be collected to estimate the parameters of the model. Finally, the estimated model can be used to perform counterfactual experiments in which the quantitative impact of an increase in female labor force participation can be estimated by taking selection and equilibrium effects into account.

We propose such an approach by developing and estimating a search model of the labor market. The model 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 dynamic, taking sample selection into account because the optimal decisions implemented by the agents are sensitive to the policy parameters. Moreover, workers' decision rules can be explicitly characterized by acknowledging some of the short-run equilibrium effects we described above. Long-run equilibrium effects can be potentially integrated in this setting if firm side data were available. As a first step, we will only use worker side data and limit our analysis to short-run equilibrium effects and some selections effects.

Search models of the labor market are widespread and influential[3] because they introduce labor market dynamics, equilibrium unemployment, and noncompetitive features as a tractable and empirically relevant model of the market. Their use in answering policy questions using microdata has a long tradition. For example, Eckstein and Wolpin (1995) studied returns to schooling; Ahn, Arcidiacono, and Wessels (2011) and Flinn (2006) evaluated the employment and welfare impact of minimum-wage legislation; Dey and Flinn (2005) analyzed the impact of employer-provided health insurance; Flabbi (2010) investigated the effects of affirmative-action legislation; and Cahuc, Postel-Vinay, and Robin (2006) evaluated the impact of workers' bargaining power. Recent contributions have used this approach to answer policy questions in LAC. Tejada (2017) focused on the distortions of introducing

[3] For a survey of theoretical literature, see Rogerson, Shimer, and Wright (2005). For a survey of empirical literature, see Eckstein and van den Berg (2007).

multiple labor contracts, and Bobba, Flabbi, and Levy (2017) assessed the effects of noncontributory benefits, informality, and long-term impacts on education.

Adapting this approach to labor markets in LAC is important to consider in the variety of labor market states present in the region. We model the large informal sector as composed by self-employed and informal employees, but we keep them in separate labor market states to capture the systematic differences in their observed labor market dynamic. Individuals are allowed to move freely 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 market utility, which is allowed to very observable characteristics.

This is considered the most important in determining its value: the presence of young children in the household. The endogeneity of the decision will make it sensitive to policy variables, allowing for the evaluation of policy experiments that consider individuals' optimal responses.

Finally, we embed in the model measures able to capture the potential impact on GDP and aggregate welfare. We accomplish this by introducing a match-specific productivity distribution that is affected by policy variables and by optimal individual behavior. This approach dates to at least Eckstein and Wolpin (1995). In gender literature, Flabbi (2010) used this to evaluate affirmative-action policies in favor of women. In LAC, Tejada and Perticara (2016) employed this method to estimate the presence of discrimination against women.

The proposed approach has two main advantages. First, we are able to deal with the two main challenges described above: sample selection and equilibrium effects. Sample selection is explicitly modeled because the participation decision is endogenous. Estimates of the out-of-labor-market utility's heterogeneity will allow for a quantitative assessment of the importance of this channel. Equilibrium effects are taken into account through two features: the optimal reservation values rules and the endogenous accepted-wage distribution.

Second, the approach merges the previous theoretical considerations with the ability to obtain labor market estimates based on microdata. We see this as an advantage with respect to quantitative exercises based on calibrated macro models such as Cuberes and Teignier's (2016) interesting exercise performed on a variety of both OECD and non-OECD countries. The advantage rests in the ability to use the full individual-level variation contained in the data and in the possibility to allow for individual-level heterogeneity when evaluating policy experiments.

Finally, it is worth noting that the two main advantages just discussed cannot be captured by methods based on a static accounting decomposition of GDP components such as the one proposed by Strategy and Co. (2012). Methods based on mechanical GDP decompositions ignore the possibilities of sample selection and equilibrium effects. Moreover, by aggregating data at the country level, they cannot exploit the individual-level variation of the data.

1.4 Structure

The paper is organized as follows. The next section provides a description of the data. Section 3 sketches out the formal economic model used in estimation. Appendix A contains more details and all the technical material. Section 4 briefly presents the estimation method and the identification strategy, while the complete treatment is relegated to Appendix B. Section 5 presents the main estimation results. Complete results are available in Appendix C. Section 6 defines and discusses the policy experiments. Section 7 concludes the study's findings.

2 Data

One additional advantage of the proposed approach is the limited-data requirement. The model can be estimated on short-panel or cross-sectional data with limited dynamic information (durations and transitions). The minimum data requirements necessary to estimate the model are:

- labor market status,

- hourly wages or earnings,
- ongoing durations in the labor market state or transition matrices between labor market states,
- demographic characteristics, and
- education or skill levels.

We use data from household surveys and employment surveys from five LAC countries: Argentina, Chile, Colombia, Mexico, and Peru. In each country, we use the latest available surveys 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. A representative household survey with a cross-sectional structure collected by the *National Institute of Statistics and Census* (INDEC), it reports information on education, labor force variables, and income. In the case of Chile, we use the 2015 *National Socio-Economic Characterization Survey* (CASEN), which was conducted between November 2015 and January 2016. It is a cross-sectional household survey that is representative at the national level and reports information on education, labor force, income, and health status. For 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, quality of life, income, and expenditures. In the case of 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 market status and demographics characteristics. Finally, we use the *National Household Survey* (ENAHO) of 2016 for Peru. It is a quarterly cross-sectional household survey that is representative at the national level and reports information on education, labor force, income, and household expenditures.

To build the estimation samples, we extract all individuals aged between 25 and 55 years old who are working in nonagricultural activities. Both restrictions ensure a more homogenous sample of workers. Labor market careers typically exhibit life-cycle patterns. Our approach is not well equipped to capture them; therefore, our age restrictions eliminates some of the major life-cycle dynamics such as retirement concerns or first entrants. A shorter age range would have guaranteed more homogeneity, but the cost, in terms of sample size, would have been too large, in particular in some countries. The compromise we reached in considering only 25- to 55-year-old participants generates an age range similar to the one used in comparable literature.[4] The focus on nonagricultural activities is dictated by the theoretical model. Our proposed model is a reliable 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; therefore, our theoretical model would not have been an appropriate description of them. 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 an employee, informally employed as an employee, and 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 he or she does not contribute to the social security system. In most LAC countries, firms are obligated to enroll salaried workers in the social security system and pay contributions that are approximately proportional to their wages. Observing this registration in labor market data is considered in the literature as a reliable measure of informal employment. Self-employed workers have typically different requirements, but they rarely enroll and pay contributions to the system. The overall informal sector is therefore frequently considered to include the self-employed and informal employees (Bobba et al., 2017; Meghir, Narita, & Robin, 2015). When considering women, we also report the presence of young children in the household.

We consider two cutoffs based on schooling age: For preschoolers, we use the cutoff at 5 years of age and, for primary and lower-secondary, at 13 years of age. In this way, we

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

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 by compulsory schooling in the region.

Tables 1 through 5 report descriptive statistics on the samples we used in estimation. Figures 1 and 2 focus on one of the features we are most interested in: participation rates. Figure 1 shows that all countries have a strong gender asymmetry in participation rates. At least 90% of men participate in the labor market in all countries, whereas female participation ranges from about 45% in Mexico to about 71% in Peru. Figure 2 shows that the overall female participation rates masks important composition effects by education. In all countries, the higher the education level, the higher the participation rate. The difference is dramatic in Argentina, Chile, and Mexico, where the differential in participation rates between women with tertiary education and women with only primary education is more than 30 percentage points.

Tables 1 through 5 report additional descriptive statistics. They include 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 U.S. dollars[5] ($\bar{w}$); and the standard deviation of wages expressed in 2016 U.S. dollars (σ_w). The unemployment durations are generally short, ranging from about to two to four months on average. The exception is Peru, where durations are extremely short—less than two months on average.[6] Gender differences in unemployment durations are typically not large.

Gender differences in average wages are, instead, significant, exhibiting the usual gender gap. As is common in other middle-income countries and high-income countries, the gender gap in average wages is increasing in education. There are few exceptions to this regularity; the largest involves informal employees with tertiary education in Mexico, where the gap is almost zero.

[5] We use the exchange rate of December 2016. We normalize the wage variables in dollars to ease the comparison between countries.
[6]Note that we do not report Argentina's average durations. The data on Argentina do not report individual unemployment durations as the other countries, only an interval to which the individual duration belongs to. Because we do not know where the duration actually is within the interval, we refrain from reporting the average. In estimation, we consider this peculiar data feature by appropriately defining the likelihood function for Argentina.

3 Model

We propose a search model of the labor market that is able to capture the specific characteristics of LAC labor markets and to account for the endogenous labor supply decisions of women. We have chosen this approach to solve some of the challenges by estimating the impact of an increase in female labor force participation on labor market outcomes and GDP (see Section 1.2).

To capture the specific characteristics of LAC labor markets, 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 lumped together in the category of informal work (see, for example, Meghir et al., 2015). However, in differentiating the informal sectors in these two distinct labor market states, we follow contributions that are more attuned to the institutional details of the region—such as Anton, Hernandez, and Levy (2012) and Bobba et al. (2017). To adapt the framework to the study of female labor force participation, we add a labor supply decision. Women's 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 (participation decision) without modeling the intensive margin (number-of-hours-worked decision) due to data limitations. Although contributions that consider both margins of the labor supply decision using similar models do exist,[7] we did not observe much about the workers' side and firms' side heterogeneity that induces differences in the intensive margin decision, so we have decided to abstract from the issue. Moreover, we will use wages per hour to estimate the structural parameters of the models so as to normalize for the differences in hours worked between men and women.

[7] See, for example, Flabbi and Mabli (2018) for the United States and Bloemen (2008) for the Netherlands.

3.1 Environment

The specific modeling environment we start with is the so-called *search-matching-bargaining model* (Eckstein & 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 individuals 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. Moreover, there are five mutually exclusive states in which each agent may be in any given point in time: nonparticipation (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 not participating, workers receive a flow utility z, which is potentially different for each agent in the economy. We model it as a draw z from the distribution $Q_i(z)$. Only unemployed workers can search for a job and receive job offers. While searching for a job, workers receive a flow utility b_i, which may be positive or negative. It is negative if search efforts and other costs related to searching and unemployment are higher than the benefit of not working. Job opportunities arrive at a specific gender- and employment-type Poisson rate λ_{ij}. If a job is accepted, subsequent job termination is possible and exogenous. Termination shocks arrive at a specific gender- and employment-type Poisson rate δ_{ij}.

A job opportunity is characterized by a match-specific productivity x, which we model as draw x from the distribution $G_{ij}(x)$. Once an employee is hired, receiving wages $w_{ij}(x)$ is considered a specific gender- and labor-related wage schedule determined by bargaining. Formal jobs are subject to have social security contributions extracted from the payroll, collected at the proportional rate τ and withdrawn at the source by firms.[8] 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. Modeling this cost is equivalent to a probabilistic one-shot cost or a deterministic flow cost. For simplicity, we use the second parameterization. The penalty is therefore modeled at a constant flow cost c. The future is discounted at a rate ρ that is common to all the agents in the economy.

[8] Note that we do not take into account the redistribution of these collected contributions within our model. In this respect, they are just a sunk cost.

3.2 Value Functions

The full formal representation of the model is presented in Appendix A. Here, we just briefly mention that the stationarity of the environment allows for a recursive characterization of the dynamic. For example, we can write the discounted value of an unemployed worker of type *i* as follows:

$$\rho U_i = b_i + \lambda_{iF} \int max[E_{iF}(x), U_i]\, dG_{iF}(x) + \lambda_{iI} \int max[E_{iI}(x), U_i]\, dG_{iI}(x)$$
$$+ \lambda_{iS} \int max[E_{iS}(x), U_i]\, dG_{iS}(x) - (\lambda_{iF} + \lambda_{iI} + \lambda_{iS})\, U_i \qquad (1)$$

The interpretation is intuitive. When a worker is unemployed, she receives utility b_i every period. Moreover, she has the possibility of meeting an employer offering a formal or an informal job (with probability λ_{iF} and λ_{iI}, respectively). Finally, the unemployed worker can take advantage of a self-employment opportunity with probability λ_{iS}. Every time she receives a job opportunity, either as an employee or as self-employed, she has the possibility to reject or accept the offer, as represented by the *max* operator over the possible labor market states. The trade-off involved in the decision is as follows. If the worker accepts the offer, she receives labor income, but if she rejects, this person may receive an even better offer in the future. All future offers are realized only when meeting a specific employer or self-employment opportunity. Therefore, the unemployed agent can only have an expectation of what those offers will be: The integral operator over the appropriate distributions define these expectations.

When a worker meets an employer, they both realize the potential productivity of that specific worker at that firm. We denote it by x. Based on this, they split the revenue the usual way: The worker receives wages, and the firm keeps the profit, which will be equal to the revenue x less than the wage paid to the worker. In addition, firms hiring legally have to pay the social security contribution τ, while firms hiring illegally set aside the illegality cost c.

The actual wage paid to the workers is decided by bargaining; that is, the employee and firm engage in making offers and counteroffers while contemplating their outside options. Their outside options are the state they will be in if they reject the offer. For the worker, this will be unemployment, and for the firm, this is the state of having a vacancy open at the firm. Additionally, workers and firms may have a stronger or weaker bargaining power, which includes other factors that may put the agents in a stronger bargaining position. We denote this parameter with β.

3.3 Wage Determination

When a worker meets an employer, they both realize the potential productivity of that specific worker at that firm. We denote it by x. Based on this, they split the revenue the usual way: The worker receives wages, and the firm keeps the profit, which will be equal to the revenue x less than the wage paid to the worker. In addition, firms hiring legally have to pay the social security contribution τ, while firms hiring illegally set aside the illegality cost c.

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The details for the solution of this bargaining problem are given in Appendix A. Here, we only mention that we assume the axiomatic Nash-bargaining solution, which leads to the following reasonably intuitive wage schedules:

$$w_{iF}(x) = \beta \frac{x}{(1+\tau)} + (1-\beta)\rho U_i \tag{2}$$

$$w_{iI}(x) = \beta(x-c) + (1-\beta)\rho U_i \tag{3}$$

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.

In conclusion, when a woman meets an employer offering a formal job generating productivity x, she will receive a wage $w_{WF}(x)$. When the offer is for an informal job, she will receive a wage $w_{WI}(x)$. When the job offer is self-employment, she will receive the entire productivity x. The same is true for men, but their wage schedules may potentially have different parameters and therefore other outside options.

3.4 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) or they stay out enjoying the utility of out-of-labor-market activities (state NP). Because women receive different utilities from these activities (z), women receiving a relatively high utility will stay out, while women receiving a relatively 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:

$$NP_i(z_i^*) = U_i \Rightarrow z_i^* = \rho U_i$$

In conclusion, all the women with $z_W < z_W^*$ participate in the labor market; all those with $z_W > z_W^*$ stay out. The same is true for men but at different parameters.

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 to search 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:

$$U_i = E_{iF}(x_{iF}^*) \Rightarrow x_{iF}^* = (1+\tau)\rho U_i \quad (4)$$

$$U_i = E_{iI}(x_{iI}^*) \Rightarrow x_{iI}^* = \rho U_i + c \quad (5)$$

$$U_i = E_{iS}(x_{iS}^*) \Rightarrow x_{iS}^* = \rho U_i \quad (6)$$

Notice that these thresholds have some economic interpretations. Employee relationships require higher productivity to be acceptable because the worker has to share with the employer. Moreover, the employer has to pay contribution or illegality costs, so the thresholds are increasing in those parameters. In conclusion, every time an unemployed woman receives a wage offer that is higher than $w_{wj}(x^*_{wj})$ or a self-employment opportunity with income higher than x^*_{wS}, she will accept. Otherwise, she will keep searching. Men, on the other hand, tend to have analogous behavior on different parameters.

These relatively simple, threshold-based, optimal decision rules can be incorporated in the value functions that then can be solved as a function of the primitive parameters. Finally, the optimal decision rules, solved value function, and steady state conditions can be used to determine the equilibrium levels of nonparticipation (n_{pi}), unemployment (u_i), and employment ($e_{i,j}$) for each gender. Again, the details are in Appendix A.

4 Identification and Estimation Method

We discuss identification and estimation based on the model we developed and the data at our disposal. As described in Section 2, we have information on labor market states, hourly wages or earnings (w), and ongoing unemployment duration (u). Each piece of information is available for each gender and for each of the three education groups we consider: primary, secondary, and tertiary schooling level.

The combination of our model and our data allows for the derivation of the likelihood contributions of each observation in our sample (see Appendix B). From the likelihood contributions, it is possible to formally prove 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 (Flinn & Heckman, 1982). The only parameters we have to normalize are the discount rate ρ, which we fix at 5% a year, and the Nash-bargaining parameter β, which we fix at the symmetric bargaining value of 0.5. Although the 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,[9] and that is why we simply calibrate the parameter to the value of symmetric Nash bargaining. This is a restriction in our context because it forces us to 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 often interpreted as capturing discrimination or gender-specific attitudes toward negotiation.[10] 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. Because the outside option enters directly in the wage equations, a lower outside option for a given gender in a schooling group translates into lower wages at the same productivity compared to the other gender.[11]

Following previous literature, we assume that the match-specific productivity distribution $G_{ij}(x)$ is lognormal with parameters (μ_{ij}, σ_{ij}). Each set of parameters is allowed to be different by country and education group on top of gender i and type of employment j. Additionally, we assume that the out-of-labor-market utility distribution $Q_i(z)$ is a negative exponent with parameter $\gamma_{i\kappa}$. 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 a household. We consider three age groups: households with at least one child aged 5 or younger ($\kappa = k5$); households with at least one child older than 5 but 13 or younger ($\kappa = k13$); and households where no children are aged 13 or younger ($\kappa = other$). After a preliminary analysis, we concluded that the estimates on men were not sensitive to the presence of children; therefore, we introduce these differences only on the women's specifications. As with the productivity distributions, each set of parameters is allowed to be different by country and education group. Finally, we allow for the presence of measurement errors in wages. We assume classic measurement error: Observed wages w^o are equal to the true wage w up to a multiplicative measurement error ϵ. We assume the log of ε is normal with mean zero and variance σ_{ME}^2.

[9] For a formal discussion, see Flinn (2006). For an example on implementation using demand-side information, see Cahuc et al. (2006).
[10] See, for example, Bartolucci (2013). Eckstein and Wolpin (1999) and Borowczyk-Martins, Bradley, and Tarasonis (2017) are examples of a similar strategy applied to racial gaps instead of gender gaps.
[11] See equations 2 and 3.

5 Estimation Results

The complete parameter estimates are reported in Appendix C. 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. Three comments about those differences are worth mentioning. First, 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, except Peru, 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, but the differences are statistically significant for all educational groups for Argentina. Finally, productivity is lower for women in formal jobs. The differences, however, are statistically significant for Argentina (in primary and secondary educational groups), Chile, and Mexico. Only in the cases of Argentina and Peru, in the tertiary educational group, are women more productive than men, but the difference is not statistically significant. In informal jobs, in turn, women are more productive than men only in the case of Argentina and for all educational groups. However, the difference is statistically significant only for the secondary educational group. In Chile (primary education) and Colombia (secondary education), women are also more productive than men in informal jobs and the differences in this case are statistically significant.

Among the structural parameters, the parameter $\gamma_{i\kappa}$ is of interest because it is the parameter governing the distribution of the utility when not 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, among tertiary educated women in Colombia, the average value of out-of-labor-market activities when children younger than 5 are present is almost 30% higher than when no children younger than 13 are present.

Tables 6 through 10 report the implications of the parameter estimate 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 3.4). The bottom panel of each table reports the 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 2 and 3. 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 4 and 5—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 GDP per worker (GDP_W) and GDP per capita (GDP_C) for each schooling and education group. 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 (a) agents may spend time in different labor market states, including unemployment; (b) agents may be less or more productive if they work formally or informally; and (c) some agents may not participate in the labor market at all. The formal definition of the measures GDP_W and GDP_C as a function of the model parameters is given in Appendix A.

The first relevant result reported in the top panel was expected: Productivity increases with education in all countries and for men and women. For example, the average productivity of formal male employees in Peru is about 6% higher if they complete secondary school with respect to primary and about 45% higher if they complete tertiary school with respect to secondary. 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 favors men, then that is not always true of the gap in productivity. For example, in

Peru, the average productivity of women with tertiary education working as formal employees is about 10% higher than the average productivity of the corresponding group of men. The gap increases to almost 30% when considering informal employees and decreases to about 3% among the self-employed.[12] It is important to notice that a gender gap in productivity in favor of women rarely translates into a similar gap in accepted wages. Again, looking at tertiary educated women in Peru, the last column of the bottom panels in Tables 6 through 10 show almost identical accepted wages between men and women working as employees and actually a significantly lower average self-employment income for women with respect to men. 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.

The bottom panels are useful to assess gender gaps in accepted wages but also to judge how well the estimated model fits the data. That is why each table reports not only the simulated moments (denoted by *Model*) but also 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 dynamic over the other labor markets states—are reported in Appendix C.

6 Policy Experiments

6.1 Definition

We propose two policy experiments that may clarify the reasons behind and the loss implied by the lower labor market participation of women with respect to men. Women may decide to participate less than men either because the value of nonparticipation is higher or because the benefit of participating in the market is lower. The first experiment relates to the first component—the value of nonparticipation—and the

[12] The gender gaps are reported in the third column of each gender-education group.

second experiment to the second component—gender asymmetries in labor market opportunities.

Opinion surveys and economic literature indicate that women value time outside the labor market more than men.[13] Our estimates show this to be the case because the average value of nonparticipation *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 childcare and child-rearing. Women still invest a higher amount of hours in childcare than men and their labor market participation is significantly affected by fertility outcomes (Burda, Hamermesh, & Weil, 2013). Many policy tools may have an impact on this value. For example, good and affordable childcare provisions may decrease the benefit of mothers' time in child-rearing and induce them to work more. Numerous policies focus on providing good and affordable childcare, using either a voucher system that provides subsidies to parents who use childcare or a direct public provision of the service.[14] To map this policy in our model, we change the parameters governing the flow utility of nonparticipation z. Recall that this value is heterogeneous in the population, but it is distributed with the cdf *Q(z)*. We estimate specific *Q(z)* for women with young children. Specifically, we allow the distribution of values of nonparticipation to be different between women with children 5 or younger, children between the age of 5 and 13, and without children younger than 13. Because childcare provision policies are more likely to affect mothers with young children, *Policy Experiment 1* reduces the average value of nonparticipation 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. Still, the reduction in half is more a reference point than an attempt to mimic specific policies implemented in the region. To gain more flexibility in this respect and to study the

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

[14] Examples of specific policies in the region include construction of preprimary school facilities in Argentina (Berlinski & Galiani, 2007); subsidized provision of after-school care in Chile (Martınez & Perticara, 2017); and a large subsidized childcare program in Colombia (Bernal & Fernandez, 2013).

possible nonlinearity of the policy impacts, we also present selected results on the same policy where we vary the average value of nonparticipation for mothers with children 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 others may relate to issues affected by policies such as human capital accumulation, gender discrimination, and 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. In this spirit, Policy Experiment 2 increases the average productivity of women in the three sectors by 10%. Because productivity is represented in our model by the distributions $G_{i,j}(x)$, formally, the experiments change 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 noting that, in many cases, a 10% increase is enough to close the gender gap in productivity. This is true in most countries among workers who completed secondary and tertiary education.[15] Among workers with only primary education, the gaps are instead 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 but arbitrary reference point. 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%.

[15] 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 to be about 20% lower than the average productivity of men. See the last column of Table 7.

6.2 Results

6.2.1 Policy Experiment 1

Figures 3 through 9 report the impact of the policy experiments on two crucial variables of interest: participation rates and GDP per capita. The impact on a larger set of variables and labor market indicators is presented in a series of tables in Appendix C. Figure 3 shows the impact of the childcare provision policy on female participation rates. The impact is positive across the board with changes ranging from 7 percentage points in Colombia to almost 9 in Peru. However, in most cases, the intervention is not enough to close the gender gap in participation.

Much of the literature looks at the impact of childcare 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) presented a review of childcare program arrangements and impacts. The policies more similar to our exercise were those providing subsidies to buy childcare services. They reviewed various studies in the United States, and they reported increases in maternal employment ranging from 5 to more than 30 percentage points. It is quite a 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 10 percentage points in the secondary group that we obtain in Peru. Baker, Gruber, and Milligan (2008) estimated the impact of a highly subsidized, universally accessible childcare provision program in Quebec. They found 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 estimation sample was about 53% at baseline. Felfe, Lechner, and Thiemann (2016) used variation in cantonal regulations of after-school care provision in Switzerland, but they found no impact on overall employment rate. However, they found some positive and significant impacts 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.

Studies have also looked at some of the countries included in our estimation sample. Berlinski and Galiani (2007) evaluated the impact of a large construction of preprimary school facilities in Argentina and found 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 because 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. Martinez and Perticara (2017) provided an identification strategy based on a randomized experiment offering after-school care, and they found 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 Martínez and Perticará's (2017) study. The increase in the participation of women in the labor market discussed so far translates into an increase in GDP because more workers contribute to production in the market. The increases in GDP per capita are reported in Figure 4 and they are substantial. For example, the GDP 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%. In addition to differences by countries, differences by education groups exist. In Argentina and Peru, 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 GDP and not yearly increases or increases in growth rate. How long it would take for the increase in GDP 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 GDP should also be interpreted on an hourly basis). However, ample evidence shows that gender differences in labor supply are not only limited to the extensive margin (the participation decision) but also include 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 the histograms of Figure 4. The total height of the histogram's columns is the "per hour" increase. Alternatively, it could be seen as the increase that would result if men and women were 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 by assigning to men and women the average amount of weekly hours observed in the data. As expected, the increases in GDP are all lower because, on average, women work fewer hours than men in all the countries, over all education levels. How much lower is denoted by the larger part of the column. However, the difference does not eliminate the large positive impact on GDP and, for many countries, 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. This robustness exercise has limitations because it does not take into account that the intensive margin could also adjust as a result of the policy. However, the adjustment in intensive margins could be either positive or negative for GDP growth depending on whether the policy increases the number of hours worked by women when they participate in the labor market or not. A definitive answer requires the full modeling and identification of the intensive margin labor supply decisions of the agents.

In the experiment discussed so far, we reduced by half the average value of nonparticipation for mothers with children aged 5 or younger. 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 nonparticipation over a broader range. Results on participation rates are reported in Figure 5 and on GDP in Figure 6. Both figures show monotone effects and 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 nonparticipation would increase female participation by 16 percentage points and GDP by 12; a reduction of 25% would increase participation by less than 4 percentage points and GDP by less than 3.

6.2.2 Policy Experiment 2

Figure 7 reports the impact of the experiment increasing women productivity by 10%. The impact 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 30 percentage points leading to full participation in the case of Peru. As expected, the impact on GDP per capita is very large among these groups, as reported in Figure 8. However, the impact on overall GDP per capita, although still large, is not as massive because the primary-education group is the least productive education group in each country. However, it is very interesting to see how the increase in GDP per capita is always larger than the increase in women's 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 9. 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 Section 1.2. In other words, it is the impact on GDP implied by the increase in participation that we have seen in Figure 7. Figure 9 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% increase in productivity increases GDP 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 the histograms of Figure 8. The lighter part of the histogram's columns considers that men and women work different hours on average when they participate in the labor market. As before, a reduction of the positive impact occurs 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 10 and 11. We perform experiments on a grid of values ranging from 1%

to 20%. The impacts on participation are more nonlinear than in the previous experiments: The elasticity decreases as we increase the average productivity. This is not the case on the GDP impact. The reason is that, as pointed out before, the overall increase in GDP 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 that is approximately linear.

At the end of the policy experiments section, we should mention a relevant limitation useful to putting 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" consist in the adjustment of the optimal decision rules for firms and workers. However, the only margins of adjustment are the reservation values that generate the equilibrium proportions in the different labor market states. Workers can therefore decide over a variety of options, but firms can only decide to accept or reject workers and to hire 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 either 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. Firms would have an optimal vacancy-posting decision that could be solved by imposing free entry. The endogenous impact on meeting rates could be incorporated by adding a matching function.[16] 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.[17] Still, our experiments show a reliable estimate of the impact of policy changes before firms can fully adjust their vacancy-posting behavior.

[16] For a review of the matching-function literature, see Petrongolo and Pissarides (2001); for a search model estimated on a LAC country using a matching function, see Bobba et al. (2017).

[17] The lack of data is exacerbated by having different schooling levels: At the minimum, we would need vacancy rates by schooling to identify the model, and this would still impose a constraint 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 as the object of our study.

7 Conclusion

Providing an estimate of the impact of an increase in female labor force participation on labor market outcomes and GDP is challenging. When performing the counterfactual exercises needed to evaluate the impact, many factors may bias the results, prominently sample selection and equilibrium effects. The approach we follow to address these challenges consists of specifying an economic model that includes some of the most important channels generating these biases, including the endogenous labor market participation decision of women. Microlevel data on Chile, Colombia, Mexico, and Peru are used to estimate the parameters of the model. Policy experiments are then implemented using the estimated model.

We focus on two policy experiments. The first approximates a childcare policy equivalent to reducing the average value of nonparticipation for mothers with young children in half. The second is equivalent to increasing average female productivity by 10%, keeping the variance constant. Both experiments generate a positive impact on female participation and—mainly through this participation increase—significant increases in GDP per capita. The first policy increases GDP per capita in the range of 4 to 6.5%; the second policy in the range of 14.8 to 25.2%. We conclude by claiming that relatively modest policies able to increase the participation of women in the labor market can provide a significant increase in GDP. However, we are not able to take into account the fiscal costs necessary to implement these policies or the possible negative externalities on household production.

References

Ahn, T., Arcidiacono, P., & Wessels, W. (2011). The distributional impacts of minimum wage increase when both labor supply and labor demand are endogenous. *Journal of Business & Economic Statistics*, *29*(1), 12–23.

Anton, A., Hernandez, F., & Levy, S. (2012). *The End of Informality in Mexico?* The Inter-American Development Bank, Wahington DC.

Baker, M., Gruber, J., & Milligan, K. (2008). Universal child care, maternal labor supply, and family well-being. *Journal of Political Economy, 116*(4), 709–745.

Bartolucci, C. (2013). Gender wage gaps reconsidered: A structural approach using matched employer-employee data. *Journal of Human Resources, 48*(4), 998–1034.

Berlinski, S., & Galiani, S. (2007). The effect of a large expansion of pre-primary school facilities on preschool attendance and maternal employment. *Labour Economics*, *14*(3), 665–680. Retrieved from http://www.sciencedirect.com/science/article/pii/S092753710700005X

Bernal, R., & Fernández, C. (2013). Subsidized childcare and child development in Colombia: Effects of *hogares comunitarios de bienestar* as a function of timing and length of exposure. *Social Science & Medicine, 97*, 241–249.

Blau, D., & Currie, J. (2006). Pre-school, day care, and after-school care: Who's minding the kids? *Handbook of the Economics of Education*, *2*, 1163–1278.

Blau, F. D., & Kahn, L. M. (2013). *Female labor supply: Why is the US falling behind?* (Technical report). National Bureau of Economic Research.

Bloemen, H. G. (2008). Job search, hours restrictions, and desired hours of work. *Journal of Labor Economics*, *26*, 137–179.

Bobba, M., Flabbi, L., & Levy, S. (2017). *Labor market search, informality and schooling investments* (Discussion Paper 11170). Institute for the Study of Labor (IZA).

Borowczyk-Martins, D., Bradley, J., & Tarasonis, L. (2017). Racial discrimination in the US labor market: Employment and wage differentials by skill. *Labour Economics, 49*, 106–127.

Burda, M., Hamermesh, D. S., & Weil, P. (2013). Total work and gender: Facts and possible explanations. *Journal of Population Economics, 26*(1), 239–261.

Busso, M., & Fonseca, D. R. (2015). Facts and determinants of female labor supply in Latin America. In L. Gasparini and M. Marchionni (Eds.), *Bridging gender gaps?* Argemtina: CEDLAS.

Cahuc, P., Postel-Vinay, F., & Robin, J. M. (2006). Wage bargaining with on-the-job search: Theory and evidence. *Econometrica*, *74*(2), 323–364.

Cuberes, D., & Teignier, M. (2016). Aggregate effects of gender gaps in the labor market: A quantitative estimate. *Journal of Human Capital, 10*(1), 1–32.

Dey, M. S., & Flinn, C. J. (2005). An equilibrium model of health insurance provision and wage determination. *Econometrica*, *73*(2), 571–627.

Eckstein, Z., & van den Berg, G. J. (2007). Empirical labor search: A survey. *Journal of Econometrics*, *136*(2), 531–564.

Eckstein, Z., & Wolpin, K. I. (1995). Duration to first job and the return to schooling: Estimates from a search-matching model. *Review of Economic Studies*, *62*(2), 263–86.

Eckstein, Z., & Wolpin, K. I. (1999). Estimating the effect of racial discrimination on first-job wage offers. *The Review of Economics and Statistics, 81*(3), 384–392.

Felfe, C., Lechner, M., & Thiemann, P. (2016). After-school care and parents' labor supply. *Labour Economics, 42*, 64–75.

Flabbi, L. (2010). Gender discrimination estimation in a search model with matching and bargaining. *International Economic Review, 51*(3), 745–783.

Flabbi, L., & Mabli, J. (2018). Household search or individual search: Does it matter? *Journal of Labor Economics, 36*(1), 1–46.

Flinn, C. (2006). Minimum wage effects on labor market outcomes under search, bargaining and endogenous contact rates. *Econometrica, 73*, 1013–1062.

Flinn, C., & Heckman, J. (1982). New methods for analyzing structural models of labor force dynamics. *Journal of Econometrics*, *18*(1), 115–168.

Kanbur, R. (2009). Conceptualizing informality: Regulation and enforcement. *Indian Journal of Labour Economics*, *52*(1), 33–42.

Levy, S. (2008). *Good intentions, bad outcomes: Social policy, informality, and economic growth in Mexico*. Washington, DC: Brooking Institution Press.

Marchionni, M. (2015). A changing scenario: Education, family, and economic environment. In L. Gasparini and M. Marchionni (Eds.), *Bridging gender gaps?* Argentina: CEDLAS.

Martínez, C., & Perticará, M. (2017). Childcare effects on maternal employment: Evidence from Chile. *Journal of Development Economics*, *126*, 127–137.

Meghir, C., Narita, R., & Robin, J. M. (2015). Wages and informality in developing countries. *American Economic Review, 105*(4), 1509–46.

Olivetti, C., & Petrongolo, B. (2008). Unequal pay or unequal employment? A cross-country analysis of gender gaps. *Journal of Labor Economics, 26*(4), 621–654.

Petrongolo, B., & Pissarides, C. A. (2001). Looking into the black box: A survey of the matching function. *Journal of Economic Literature, 39*(2), 390–431.

Rogerson, R., Shimer, R., & Wright, R. (2005). Search-theoretic models of the labor market: A survey. *Journal of Economic Literature, 43*(4), 959–988.

Scandura, T. A., & Lankau, M. J. (1997). Relationships of gender, family responsibility and flexible work hours to organizational commitment and job satisfaction. *Journal of Organizational Behavior*, 377–391.

Strategy and Co. (2012). *Empowering the third billion: Women and the world of work in 2012*.

Tejada, M. M. (2017). Dual labor markets and labor protection in an estimated search and matching model. *Labour Economics, 46*, 26–46.

Tejada, M., & Perticara, M. (2016). Sources of gender wage gaps for skilled workers in Latin American countries (Working Paper 317). ILADES, Universidad Alberto Hurtado.

Table 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	-	-	-	311	0.04	-	-	-
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	-	-	-	219	0.05	-	-	-
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	-	-	-	252	0.04	-	-	-
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 they are reported in U.S. dollars as of December 2016 (exchange rate = 15.8620 Argentinian pesos/U.S. dollar). A worker is categorized as informal if he or she reports not having benefits of social security. K means proportion of women with the presence of children in the household with respect to nonparticipating women. Unemployment durations ($\bar{t}_u$) are only observed in time intervals.

Table 2: 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 they are reported in U.S. dollars as of December 2016 (exchange rate = 667.17 Chilean pesos/U.S. dollar). A worker is categorized as informal if he or she reports not having benefits of social security. K means proportion of women with the presence of children in the household with respect to nonparticipating women.

Table 3: 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 they are reported in U.S. dollars as of December 2016 (exchange rate = 3009.86 Colombian pesos/U.S. dollar). A worker is categorized as informal if he or she reports not having benefits of social security. K means proportion of women with the presence of kids in the household with respect to nonparticipating women.

Table 4: Mexico - 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	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 they are reported in U.S. dollars as of December 2016 (exchange rate = 20.52 Mexican pesos/U.S. dollar). A worker is categorized as informal if he or she reports not having access to health care. K means proportion of women with the presence of children in the household with respect to nonparticipating women.

Table 5: Peru - 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	60	0.02	1.04	-	-	102	0.02	0.74	-	-
Formal Emp.	631	0.18	-	1.95	0.99	192	0.03	-	1.37	0.54
Informal Emp.	981	0.29	-	1.52	0.77	581	0.09	-	1.01	0.62
Self-Emp.	1447	0.42	-	1.86	1.68	3198	0.52	-	1.06	1.20
Non Part.	319	0.09	-	-	-	2059	0.34	-	-	-
$K \leq 5$						1014	0.49			
$5 < K \leq 13$						533	0.26			
Education Group: Secondary										
Unemployed	121	0.02	1.14	-	-	94	0.02	0.72	-	-
Formal Emp.	1659	0.33	-	2.28	1.23	485	0.11	-	1.79	1.04
Informal Emp.	1023	0.20	-	1.62	0.84	641	0.15	-	1.21	0.71
Self-Emp.	1966	0.39	-	2.21	2.10	1670	0.39	-	1.50	1.72
Non Part.	270	0.05	-	-	-	1429	0.33	-	-	-
$K \leq 5$						716	0.50			
$5 < K \leq 13$						384	0.27			
Education Group: Tertiary										
Unemployed	236	0.04	1.31	-	-	259	0.04	1.12	-	-
Formal Emp.	3685	0.57	-	3.82	2.60	3061	0.44	-	3.54	2.16
Informal Emp.	627	0.10	-	2.18	1.57	730	0.11	-	1.77	1.32
Self-Emp.	1588	0.24	-	3.48	3.88	1380	0.20	-	2.27	2.96
Non Part.	383	0.06	-	-	-	1468	0.21	-	-	-
$K \leq 5$						717	0.49			
$5 < K \leq 13$						361	0.25			

Note. Wage distributions are trimmed at the top and bottom 1 percentile by gender, education group, and type of job, and they are reported in U.S. dollars as of December 2016 (exchange rate = 3.395 soles/U.S. dollar). A worker is categorized as informal if he or she reports not having access to health care. K means proportion of women with the presence of children in the household with respect to nonparticipating women.

Table 6: Argentina - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	4.493	3.788	0.843	5.134	4.731	0.922	6.753	6.689	0.990
$SD(x_F)$									
Model	0.024	0.021	0.849	0.010	0.018	1.783	0.009	0.005	0.631
$E[x_I]$									
Model	2.494	2.638	1.058	2.853	2.796	0.980	4.677	4.259	0.911
$SD[x_I]$									
Model	0.680	1.070	1.574	1.524	1.761	1.156	8.133	5.026	0.618
$E[x_S]$									
Model	3.013	2.413	0.801	3.525	3.197	0.907	5.263	5.428	1.031
$SD[x_S]$									
Model	1.758	1.880	1.069	2.204	2.781	1.261	3.931	4.786	1.217
GDP_W									
Model	7.189	7.035	0.979	9.025	8.151	0.903	13.462	14.111	1.048
GDP_C									
Model	6.107	3.113	0.510	8.201	4.627	0.564	11.980	10.647	0.889
$E[w\|e_F]$									
Data	4.492	3.783	0.842	5.095	4.662	0.915	6.728	6.642	0.987
Model	4.524	3.769	0.833	5.161	4.760	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	0.964	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	2.499	2.640	1.057	2.841	2.810	0.989	4.565	4.287	0.939
$SD[w\|e_I]$									
Data	1.329	1.559	1.173	1.645	1.782	1.083	2.957	2.774	0.938
Model	1.402	1.695	1.209	2.146	2.524	1.176	6.630	5.910	0.891
$E[w\|e_S]$									
Data	2.997	2.365	0.789	3.520	3.156	0.897	5.207	5.228	1.004
Model	3.034	2.434	0.802	3.524	3.185	0.904	5.284	5.432	1.028
$SD[w\|e_S]$									
Data	2.269	2.184	0.962	2.771	3.206	1.157	4.360	4.770	1.094
Model	2.517	2.296	0.912	3.056	3.521	1.152	5.322	6.019	1.131

Note. $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, GDP_W is the GDP per worker, GDP_C is the GDP 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 7: Chile - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	5.080	4.936	0.972	5.823	5.134	0.882	13.382	10.585	0.791
$SD(x_F)$									
Model	0.030	0.410	13.464	0.029	0.021	0.740	1.888	0.115	0.061
$E[x_I]$									
Model	0.916	4.115	4.490	0.692	0.580	0.838	1.018	0.806	0.792
$SD[x_I]$									
Model	2.301	1.852	0.805	1.511	1.711	1.132	3.111	6.594	2.119
$E[x_S]$									
Model	2.034	2.345	1.153	0.785	1.429	1.821	4.441	3.217	0.724
$SD[x_S]$									
Model	1.630	2.243	1.376	1.420	2.706	1.906	5.734	5.427	0.946
GDP_W									
Model	4.206	3.715	0.883	5.265	4.489	0.853	12.261	10.059	0.820
GDP_C									
Model	3.279	1.161	0.354	4.614	2.405	0.521	10.319	7.312	0.709
$E[w\|e_F]$									
Data	2.676	2.126	0.794	3.262	2.566	0.787	7.312	5.501	0.752
Model	2.698	2.121	0.786	3.254	2.594	0.797	7.210	5.481	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	1.114	0.634	0.569	1.463	0.998	0.682	5.620	3.600	0.641
$E[w\|e_I]$									
Data	2.315	2.004	0.866	2.798	2.372	0.848	5.730	4.983	0.870
Model	2.346	1.993	0.850	2.913	1.885	0.647	6.280	5.542	0.882
$SD[w\|e_I]$									
Data	1.122	1.381	1.232	1.707	1.560	0.914	5.458	3.787	0.694
Model	2.413	1.122	0.465	2.863	1.846	0.645	8.766	9.735	1.110
$E[w\|e_S]$									
Data	2.632	2.328	0.885	3.457	2.842	0.822	8.091	6.199	0.766
Model	2.666	2.337	0.877	3.449	2.956	0.857	8.037	6.569	0.817
$SD[w\|e_S]$									
Data	2.020	2.289	1.133	3.110	2.764	0.889	9.040	6.670	0.738
Model	2.092	2.370	1.133	3.348	3.594	1.073	9.589	8.445	0.881

Note. $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, GDP_W is the GDP per worker, GDP_C is the GDP 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 8: 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	3.217	0.978	2.762	3.072	1.112	6.759	6.125	0.906
$SD(x_F)$									
Model	0.801	0.015	0.018	0.005	0.002	0.361	4.674	0.103	0.022
$E[x_I]$									
Model	2.218	1.814	0.818	0.717	1.773	2.472	0.475	0.467	0.983
$SD[x_I]$									
Model	0.790	0.0150	0.019	0.601	0.373	0.620	0.730	0.664	0.909
$E[x_S]$									
Model	1.132	0.836	0.738	0.500	0.319	0.637	2.355	2.360	1.002
$SD[x_S]$									
Model	0.671	0.614	0.915	0.547	1.216	2.222	2.734	2.030	0.743
GDP_W									
Model	1.714	1.301	0.759	2.041	1.821	0.892	5.200	4.786	0.920
GDP_C									
Model	1.480	0.626	0.423	1.817	1.086	0.598	4.393	3.421	0.779
$E[w\|e_F]$									
Data	1.306	1.169	0.895	1.448	1.305	0.902	3.055	2.775	0.908
Model	1.300	1.242	0.955	1.452	1.336	0.920	3.045	2.760	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	0.375	0.500	1.333	0.518	0.463	0.895	2.315	1.897	0.819
$E[w\|e_I]$									
Data	1.082	0.870	0.804	1.127	0.976	0.866	1.411	1.282	0.908
Model	1.087	0.840	0.772	1.105	0.974	0.882	1.392	1.288	0.925
$SD[w\|e_I]$									
Data	0.386	0.359	0.928	0.407	0.352	0.866	0.793	0.683	0.861
Model	0.430	0.335	0.778	0.556	0.393	0.707	0.983	1.114	1.133
$E[w\|e_S]$									
Data	1.122	0.805	0.717	1.398	1.067	0.763	2.985	2.599	0.871
Model	1.131	0.839	0.741	1.405	1.230	0.875	3.066	2.728	0.890
$SD[w\|e_S]$									
Data	0.658	0.572	0.870	0.912	0.845	0.926	2.734	2.338	0.855
Model	0.698	0.741	1.061	0.975	2.037	2.090	3.380	3.057	0.904

Note. $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, GDP_W is the GDP per worker, GDP_C is the GDP 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 9: Mexico - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	3.679	2.896	0.787	2.898	2.796	0.965	6.166	6.097	0.989
$SD(x_F)$									
Model	0.423	0.342	0.809	0.010	0.053	5.441	0.111	0.139	1.251
$E[x_I]$									
Model	2.504	2.122	0.848	1.334	1.120	0.840	1.124	0.982	0.873
$SD[x_I]$									
Model	0.409	0.767	1.876	0.616	0.998	1.619	1.286	1.654	1.286
$E[x_S]$									
Model	1.693	1.193	0.705	1.050	0.462	0.440	2.304	0.633	0.275
$SD[x_S]$									
Model	0.946	1.057	1.118	1.063	0.984	0.926	1.987	1.287	0.648
GDP_W									
Model	2.683	1.858	0.693	2.387	2.229	0.934	5.194	5.193	1.000
GDP_C									
Model	2.218	0.552	0.249	2.121	0.917	0.432	4.346	3.064	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	1.420	1.126	0.793	1.587	1.390	0.876	3.019	2.874	0.952
$SD[w\|e_F]$									
Data	0.588	0.437	0.744	0.748	0.690	0.922	1.852	1.630	0.881
Model	0.575	0.391	0.680	0.725	0.644	0.888	1.907	1.735	0.910
$E[w\|e_I]$									
Data	1.216	1.040	0.855	1.288	1.148	0.891	2.091	2.020	0.966
Model	1.216	1.032	0.849	1.294	1.136	0.878	2.138	2.046	0.957
$SD[w\|e_I]$									
Data	0.517	0.628	1.216	0.663	0.672	1.013	1.574	1.483	0.942
Model	0.517	0.526	1.018	0.663	0.794	1.196	1.709	1.922	1.125
$E[w\|e_S]$									
Data	1.672	1.175	0.703	1.988	1.674	0.842	3.171	2.636	0.831
Model	1.700	1.203	0.708	1.968	1.710	0.869	3.175	2.705	
$SD[w\|e_S]$									
Data	1.137	1.039	0.914	1.575	1.634	1.037	2.902	2.620	0.903
Model	1.214	1.168	0.962	1.581	2.029	1.284	3.049	3.203	1.051

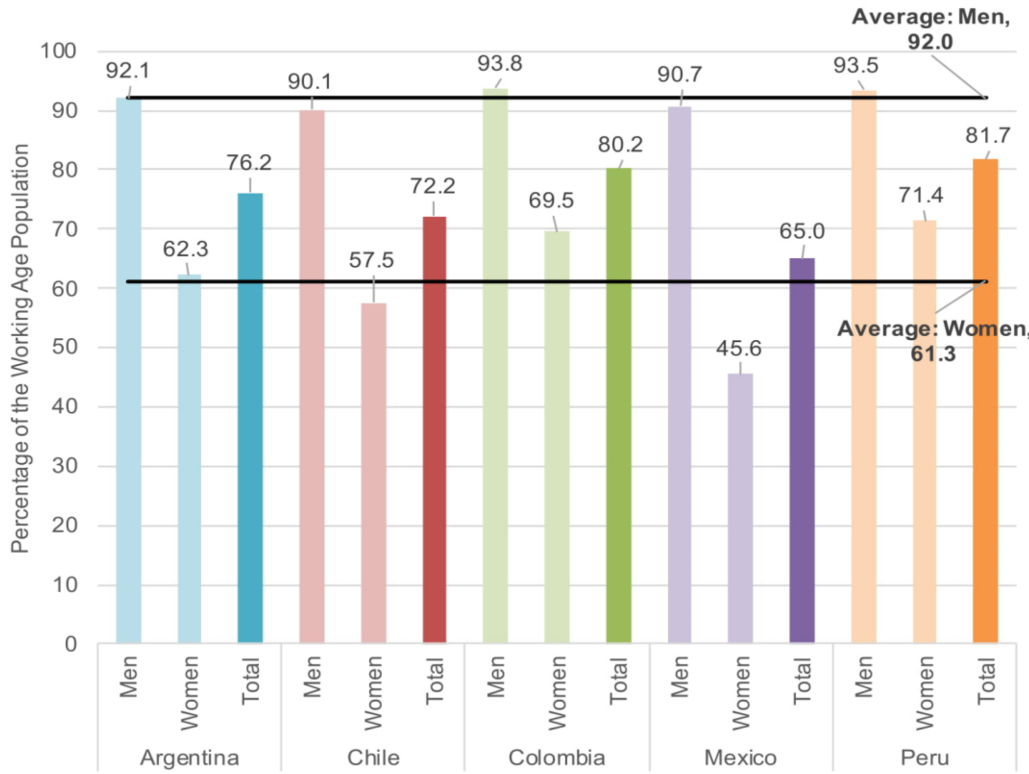
Note. $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, GDP_W is the GDP per worker, GDP_C is the GDP per capita, $E[w|e]$ is the average wage conditional on the employment status e, and finally $SD[w|e]$ is the standard deviation of wages conditioning in the employment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

Table 10: Peru - Productivity and Wages

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	5.114	3.904	0.764	5.417	4.661	0.860	7.852	8.685	1.106
$SD(x_F)$									
Model	0.028	0.112	3.978	0.017	0.016	0.988	0.170	0.035	0.203
$E[x_I]$									
Model	3.327	2.267	0.681	3.211	2.712	0.845	1.024	1.327	1.296
$SD[x_I]$									
Model	0.008	0.002	0.241	0.023	0.010	0.451	1.569	8.283	5.281
$E[x_S]$									
Model	1.912	2.760	1.443	2.177	2.439	1.120	1.396	1.443	1.034
$SD[x_S]$									
Model	1.265	9.382	7.418	1.113	6.015	5.407	2.497	3.624	1.451
GDP_W									
Model	3.126	2.859	0.915	3.409	3.085	0.905	6.210	6.464	1.041
GDP_C									
Model	2.785	1.828	0.657	3.148	2.015	0.640	5.620	4.842	0.862
$E[w\|e_F]$									
Data	1.954	1.369	0.700	2.277	1.794	0.788	3.822	3.540	0.926
Model	2.110	1.570	0.744	2.437	1.996	0.819	3.827	3.760	0.983
$SD[w\|e_F]$									
Data	0.987	0.539	0.546	1.234	1.037	0.841	2.598	2.165	0.833
Model	1.380	1.164	0.843	1.582	1.464	0.925	2.546	2.732	1.073
$E[w\|e_I]$									
Data	1.525	1.006	0.660	1.623	1.211	0.746	2.185	1.771	0.811
Model	1.611	1.059	0.657	1.736	1.346	0.775	2.201	2.314	1.051
$SD[w\|e_I]$									
Data	0.765	0.617	0.806	0.836	0.707	0.847	1.571	1.319	0.840
Model	1.073	0.750	0.699	1.162	0.958	0.824	2.193	5.408	2.467
$E[w\|e_S]$									
Data	1.858	1.060	0.570	2.206	1.502	0.681	3.480	2.275	0.654
Model	1.908	2.857	1.497	2.166	2.705	1.249	3.529	2.585	0.732
$SD[w\|e_S]$									
Data	1.684	1.195	0.710	2.103	1.719	0.818	3.881	2.961	0.763
Model	1.981	9.876	4.985	1.956	6.607	3.378	4.987	5.321	1.067

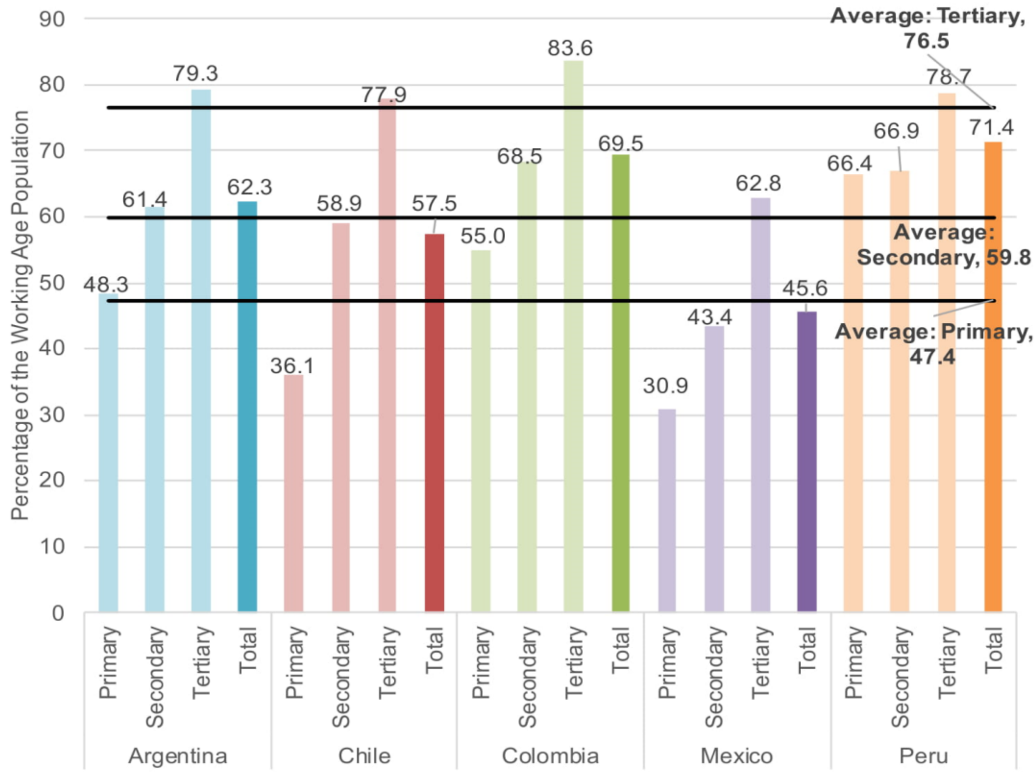
Note. $E[x]$ is the average productivity, $SD(x)$ is the standard deviation of productivity, GDP_W is the GDP per worker, GDP_C is the GDP per capita, $E[w|e]$ is the average wage conditional on the employment status e, and finally $SD[w|e]$ is the standard deviation of wages conditioning in the employment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

Figure 1: Participation Rates by Gender



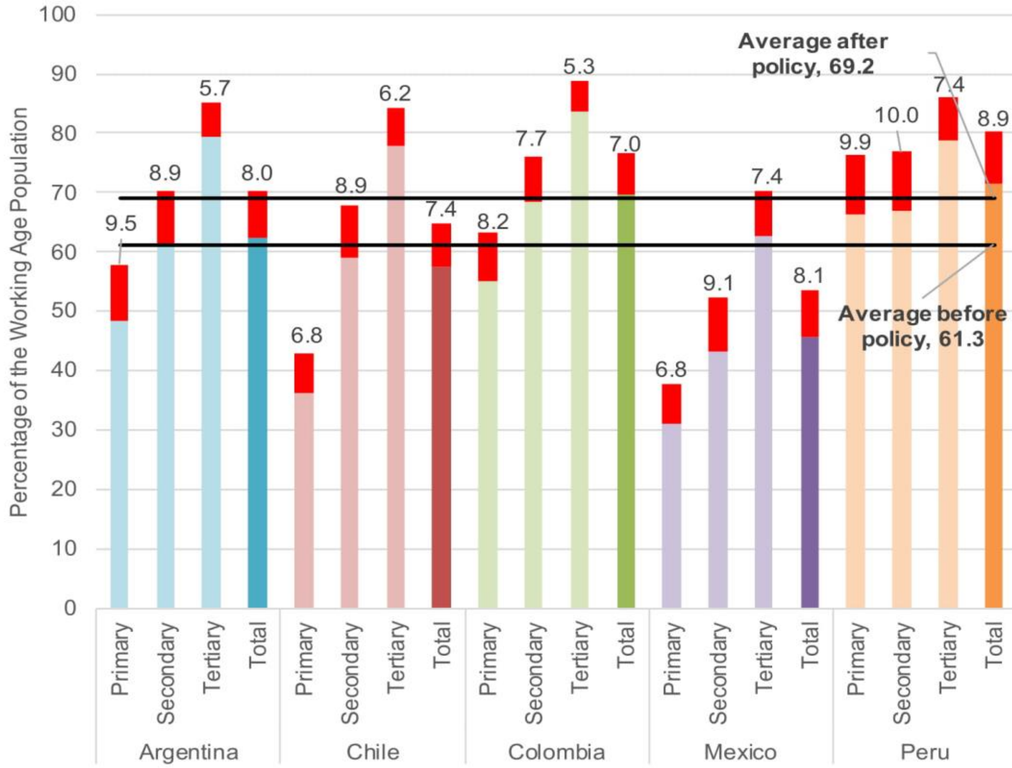
Note: Values are computed based on the estimation samples for each country. See Section 2 for data sources.

Figure 2: Female Participation Rates by Education



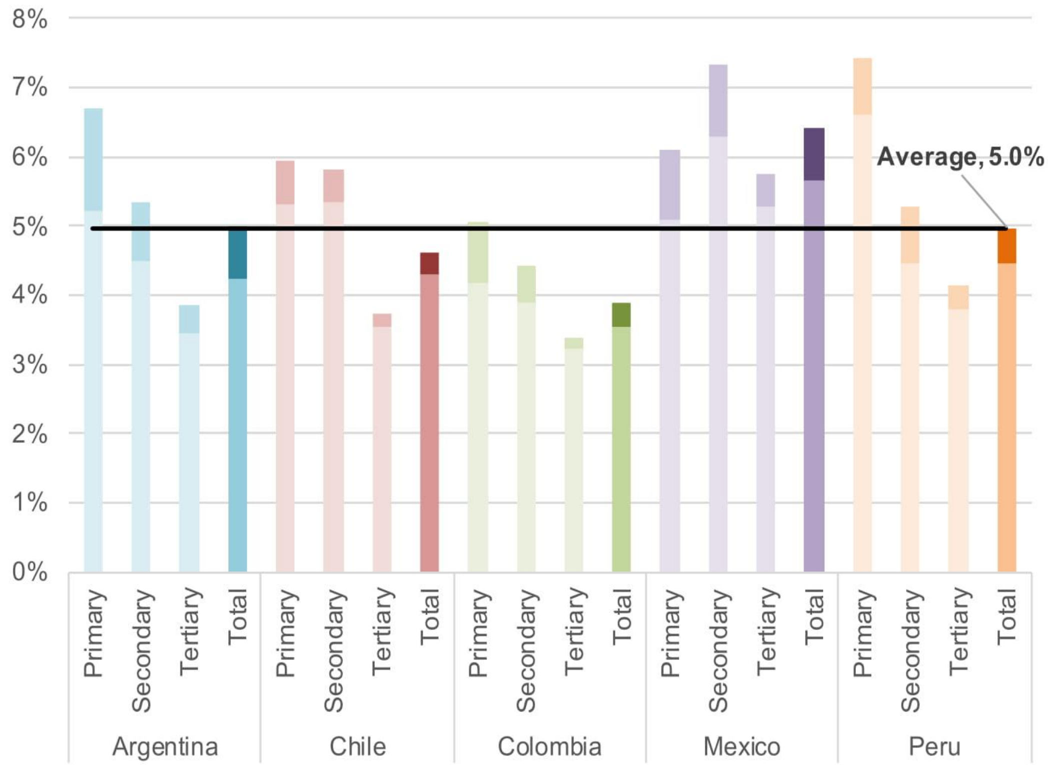
Note: Values are computed based on the estimation samples for each country. See Section 2 for data sources.

Figure 3: Childcare Provision Policy: Impact on Female Participation Rates



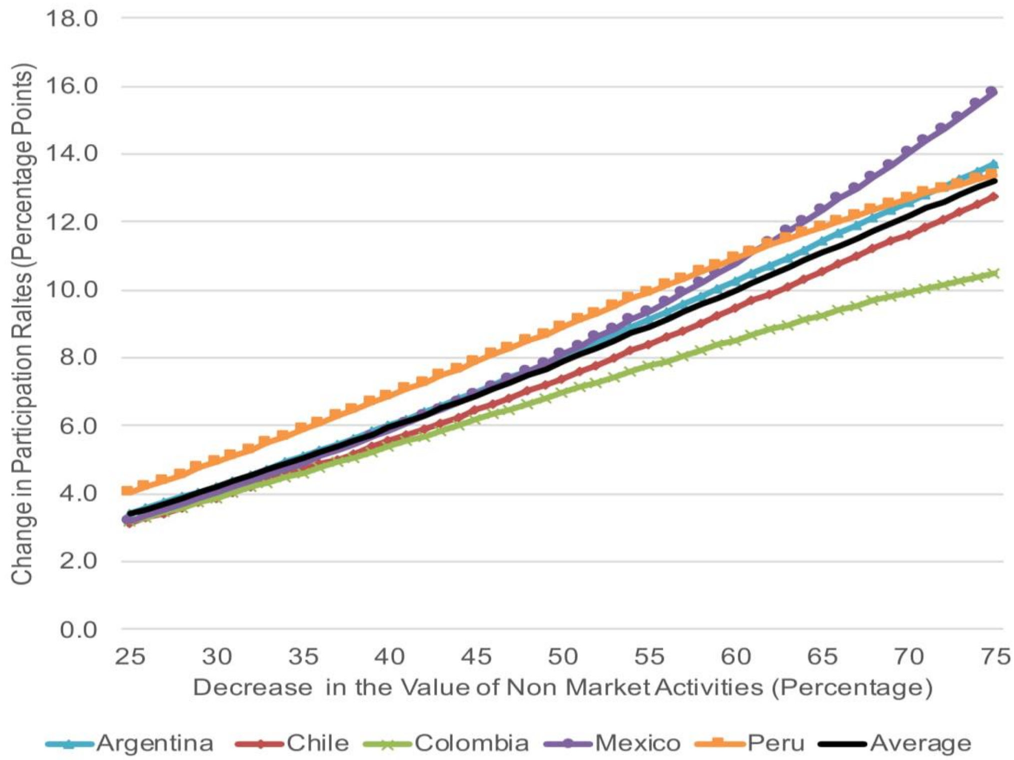
Note: The overall length of the column is the post policy participation rate. The darker red segment is the impact of the policy. The number on top of each column is the percent change in participation rates post policy (i.e., the length of the darker red segment). The policy reported is *Policy Experiment 1*: reducing by half the average value of nonparticipation for mothers with children aged 5 or younger. See Section 6 for more details.

Figure 4: Childcare Provision Policy: Impact on GDP per Capita



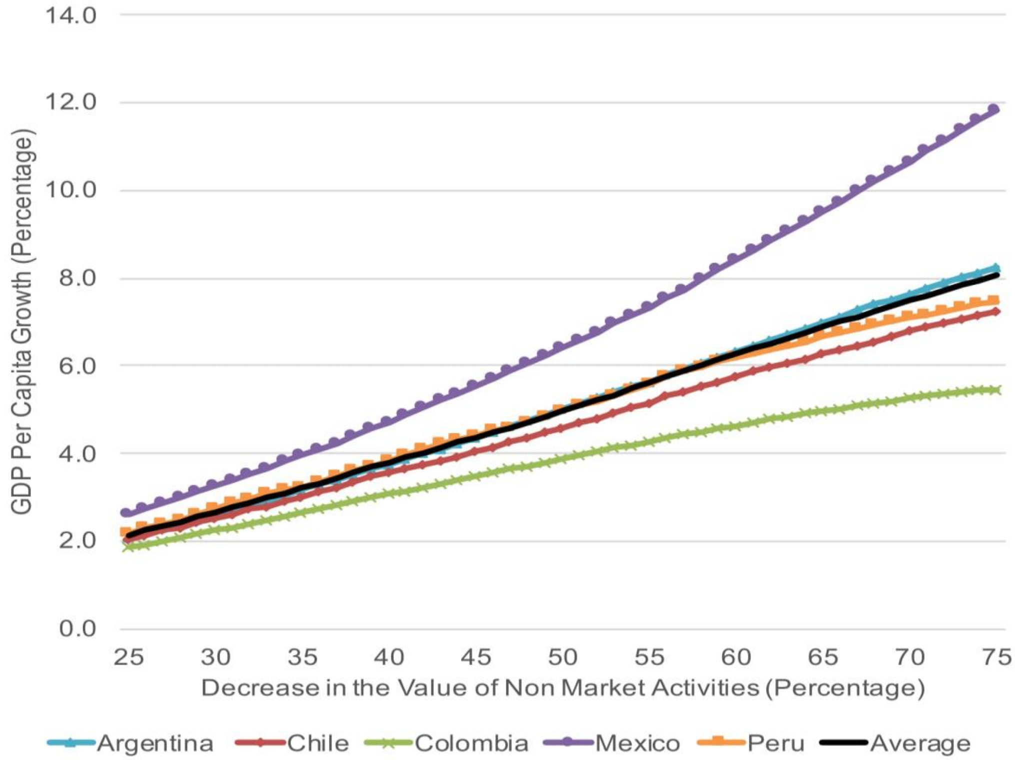
Note: Figure reports percent changes in GDP per capita as a result of *Policy Experiment 1*: reducing by half the average value of nonparticipation for mothers with children aged 5 or younger. Lightly colored bars represent the effect on GDP considering differences in average weekly hours worked by men and women. See Section 6 for more details.

Figure 5: Childcare Provision Policy: Impact on Female Participation Rates



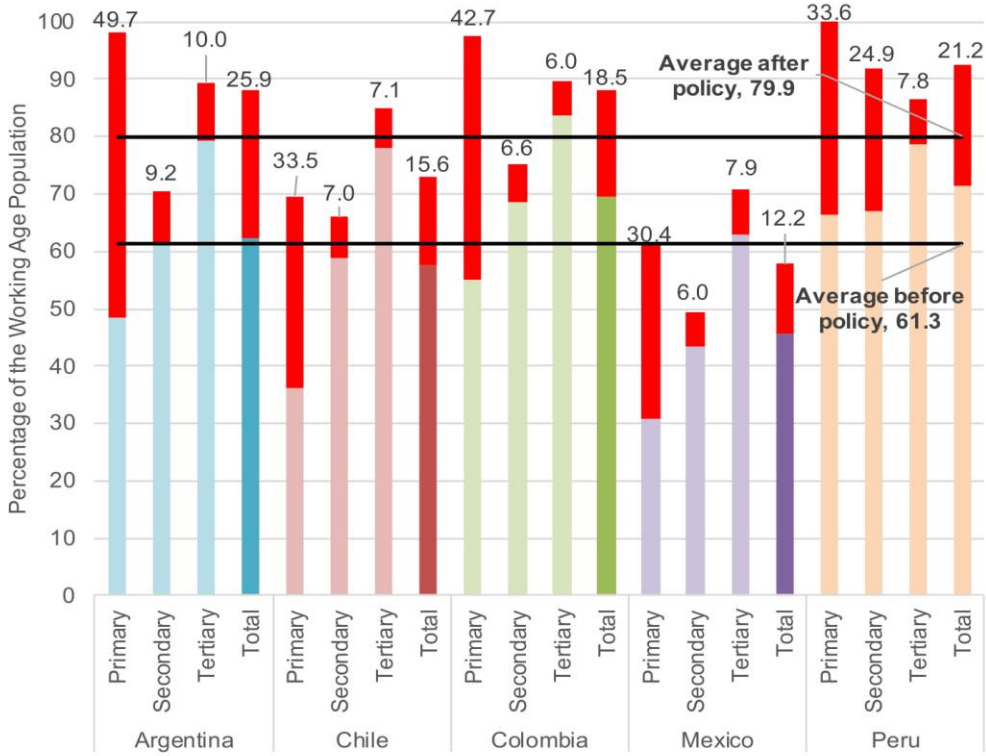
Note: Figure reports percent changes in female participation rates as a result of *Policy Experiment 1*: a range between 25% and 75% of reductions in the average value of nonparticipation for mothers with children aged 5 or younger. See Section 6 for more details.

Figure 6: Childcare Provision Policy: Impact on GDP per Capita



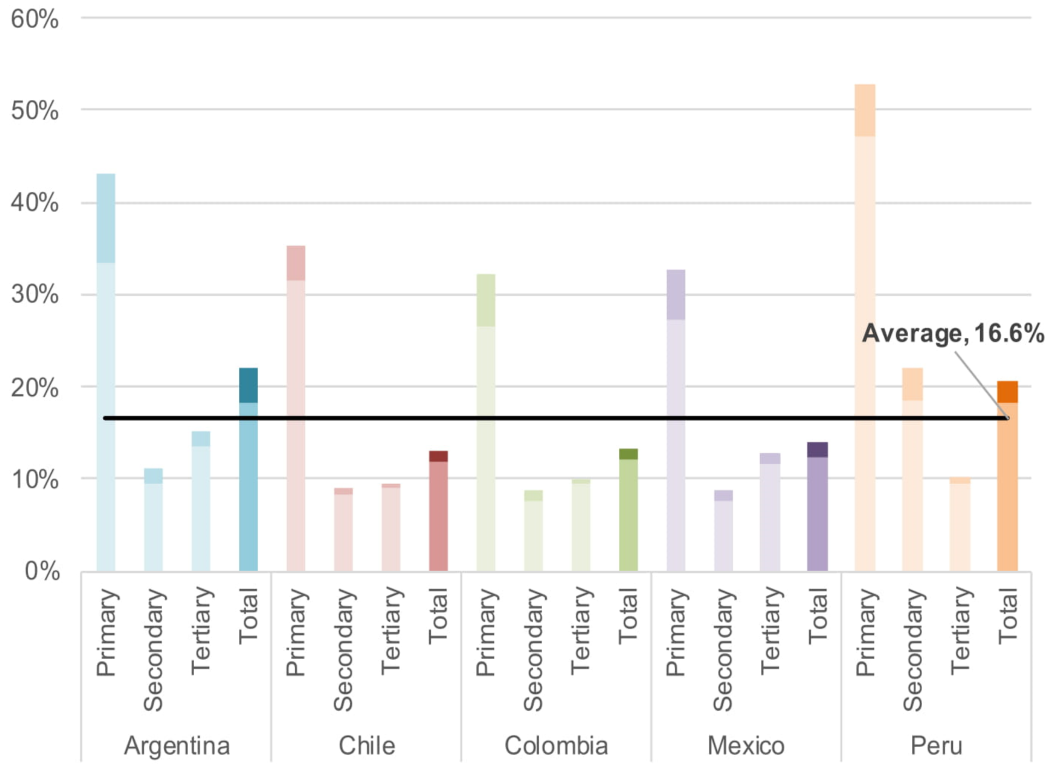
Note: Figure reports percent changes in GDP per capita as a result of *Policy Experiment 1*: a range between 25% and 75% of reductions in the average value of nonparticipation for mothers with children aged 5 or younger is considered. See Section 6 for more details.

Figure 7: Increased Female Productivity Policy: Impact on Female Participation Rates



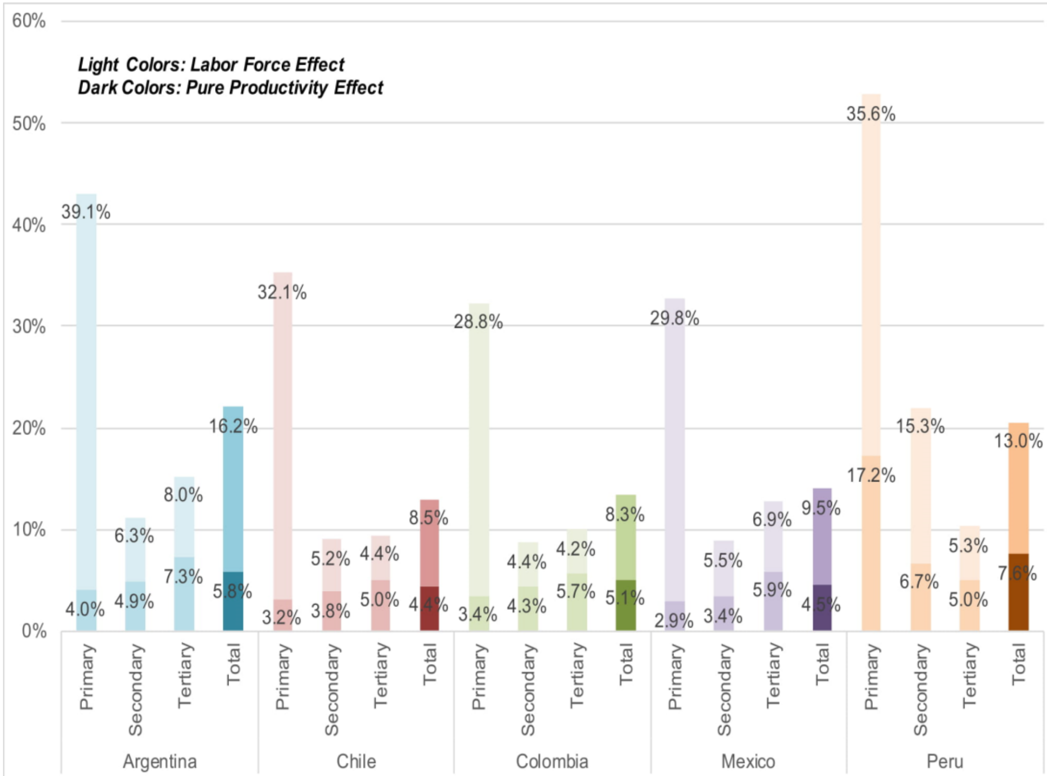
Note: The overall length of the column is the post policy participation rate. The darker red segment is the impact of the policy. The number on top of each column is the percent change in participation rates post policy (i.e., the length of the darker red segment). The policy reported is *Policy Experiment 2*: increasing the average productivity of women by 10%, keeping the variance of the productivity constant. See Section 6 for more details.

Figure 8: Increased Female Productivity Policy: Impact on GDP per Capita



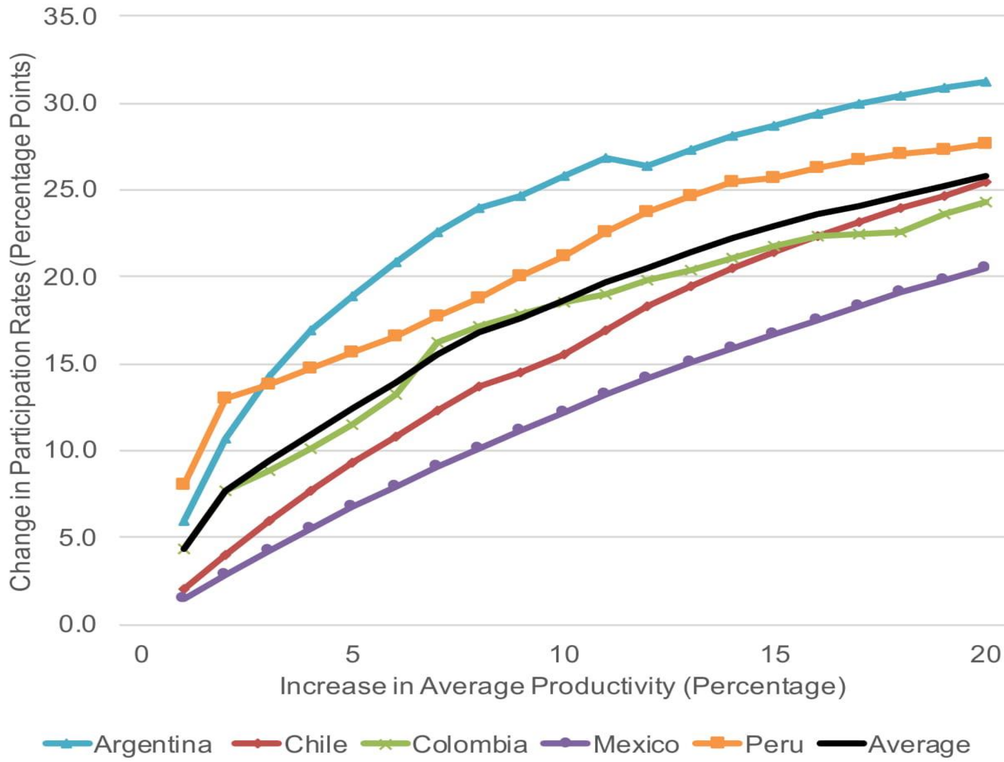
Note: Figure reports percent changes in GDP per capita as a result of *Policy Experiment 2*: increasing the average productivity of women by 10%. Lightly colored bars represent the effect on GDP considering differences in average weekly hours worked by men and women. See Section 6 for more details.

Figure 9: Increased Female Productivity Policy: Impact on GDP per Capita by Channel



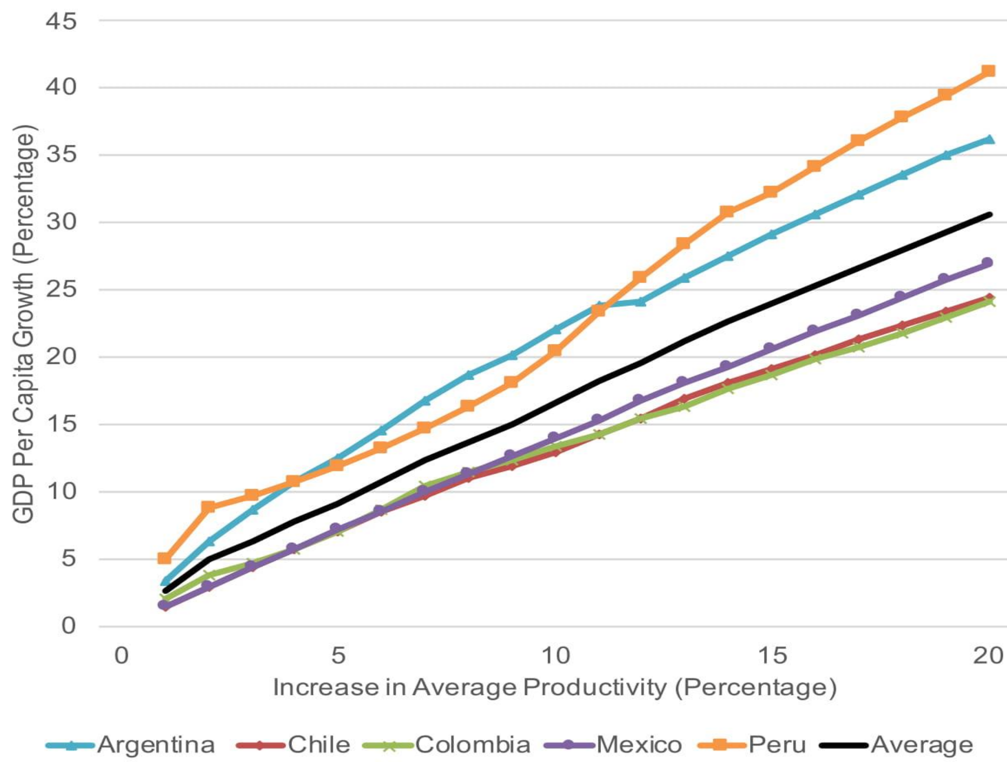
Note: Figure reports percent changes in GDP per capita as a result of *Policy Experiment 2:* increasing the average productivity of women by 10%. See Section 6 for more details. The overall increase is decomposed in this portion due to the 10% productivity increase (pure productivity effect) and the portion due to the increase in participation resulting from the productivity increase (labor force effect).

Figure 10: Increased Female Productivity Policy: Impact on Female Participation Rates



Note: Figure reports percent 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 11: Increased Female Productivity Policy: Impact on GDP per Capita



Note: Figure reports percent changes in GDP per capita 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.

Appendix

A Model

A.1 Environment

The environment is characterized by stationarity, continuous time, and infinitely lived individuals. There are two types of workers: $i = M, W$. There are five mutually exclusive states in which agents may be classified: nonparticipation *(NP)*, unemployment *(U)*, formal employment *(F)*, informal employment *(I)*, or self-employment *(S)*.

When nonparticipating, workers receive a flow utility z, where $z \sim Q_i(z)$ with $i = M, W$.

Only unemployed workers can search for a job and receive job offers. While searching for a job, workers receive a flow (dis)utility b_i with $i = M, W$. Job opportunities arrive at a gender- and employment-type specific Poisson rate λ_{ij}, with $i = M, W$ and $j = F, I, S$. 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 specific gender- and labor-related wage schedule determined by bargaining. Formal jobs are subject to a payroll social security contribution, collected at the proportional rate τ and withdrawn at the source by firms. Collected contributions are not redistributed among workers and are just a sunk cost. Informal jobs do not pay social security contributions, but they face the risk of being caught, which involves a penalty. The penalty has to be paid by the firm. This penalty is modeled as a constant flow cost c. The future is discounted at a rate ρ common to all the agents in the economy.

A.2 Value Function

The gender-specific flow value for an individual deciding not to participate in the labor market $\rho NPi(z)$ is the flow utility received by the individual for engaging in nonmarket activities z, that is:

$$\rho NP_i(z) = z, \qquad i = M, W \qquad (A.1)$$

If the individual decides to participate, the gender-specific flow value of participating in the labor market is characterized by the flow value of an unemployed individual searching for a job ρU_i, that is:

$$\rho U_i = b_i + \lambda_{iF} \int max[E_{iF}(x), U_i]\, dG_{iF}(x) + \lambda_{iI} \int max[E_{iI}(x), U_i]\, dG_{iI}(x)$$
$$+ \lambda_{iS} \int max[E_{iS}(x), U_i]\, dG_{iS}(x) - (\lambda_{iF} + \lambda_{iI} + \lambda_{iS})U_i,$$
$$i = M, W \qquad (A.2)$$

In each instant of time, an unemployed individual receives a flow utility b_i and may meet a formal or an informal potential employee or receive a self-employment job opportunity. Meetings with formal firms, informal firms, and self-employment opportunities arrive at Poisson rates λ_{iF}, λ_{iI}, and λ_{iS}, respectively. If a job opportunity of any type arrives, a match-specific productivity x is drawn from the corresponding productivity distribution $G_{ij}(x)$, with $i = M, W$ and $j = F, I, S$. Note that the formality status in this model is assumed to be exogenous. For any type of job, the worker accepts the potential match if and only if the value of working at that productivity $E_{ij}(x)$ is higher than the value of staying in the unemployment state U_i (this is captured by the maximum operator). Finally, if no job opportunity arrives, the individual remains unemployed and continues searching for a job.

The gender-specific flow values of working as a formal employee, as an informal employee, or as self-employed in a match with specific productivity x are $\rho E_{iF}(x)$, $\rho E_{iI}(x)$, and $\rho EiS(x)$, respectively (with $i = M, W$), and are characterized as:

$$\rho E_{iF}(x) = w_{iF}(x) + \delta_{iF}[U_i - E_{iF}(x)] \qquad (A.3)$$
$$\rho E_{iI}(x) = w_{iI}(x) + \delta_{iI}[U_i - E_{iI}(x)] \qquad (A.4)$$
$$\rho E_{iS}(x) = x + \delta_{iS}[U_i - E_{iS}(x)] \qquad (A.5)$$

Employees in a formal or an informal job receive a wage rate of $w_{iF}(x)$ and $w_{iI}(x)$, respectively, while self-employed workers receive what they produce (x). Additionally, in all types of jobs, exogenous destruction shocks arrive at Poisson rate δ_{ij}, $j = F, I, S$. In that case, the match is dissolved, and the individual becomes unemployed and a loss of value of $U_i - E_{ij}(x)$ is realized.

On the demand side, the gender-specific flow values of filled vacancies, both formal $\rho J_{iF}(x)$ and informal $\rho J_{iI}(x)$, with an individual productivity of x are characterized by:

$$\rho J_{iF}(x) = x - (1+\tau)w_{iF}(x) - \delta_{iF}J_{iF}(x) \qquad (A.6)$$
$$\rho J_{iI}(x) = x - w_{iI}(x) - c - \delta_{iI}J_{iI}(x) \qquad (A.7)$$

In the case of a formal firm, the instantaneous profit $x - (1+\tau)w_{iF}(x)$ takes into account that the firm has to pay a proportional payroll tax τ (the social security contribution). The informal firm does not pay taxes, but the parameter c is incorporated in the instantaneous profit, $x - w_{iI}(x) - c$, to take into account any cost of hiring informally (for example, legal penalties). In any type of firm, a termination shock arrives at Poisson rate δ_{ij} ($j = F, I$). If that is the case, the match is terminated and a loss of value of $J_{ij}(x)$ is realized.

A.3 Equilibrium

A.3.1 Nonparticipation Decision

An individual deciding whether to participate in the labor market solves the following problem:

$$\max \{NP_i(z), U_i\}$$

Because $NP_i(z)$ is increasing z and U_i is constant, the solution of the maximization problem has a reservation value property. For high values of z, we have that $NP_i(z) \geq U_i$; therefore, the optimal decision would be not to participate, while for lower values of z, for which $NP_i(z) < U_i$, the opposite will occur. Let z^* be the utility level that makes the individual indifferent between participating in the labor market and not participating, then:

$$NP_i(z^*) = U_i \Rightarrow \rho NP_i(z^*) = \rho U_i \Rightarrow z^* = \rho U_i$$

The decision rule for the individual in terms of the reservation value would be to participate if $z <= z^* = \rho U_i$ (he or she gets a lower flow utility outside of the market than when searching for a job), and not to participate otherwise.

A.3.2 Wage Determination

Individuals and potential employers meet on a bilateral basis, and therefore wages are the result of a bargaining process. We used the generalized axiomatic Nash bilateral bargaining outcome to determine wages, which 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 their bargaining power. Let $S_{ij}(x)$, with $i = M, W$ and $j = F, I, S$, be the gender-specific total surplus by type of job of a match with productivity x, then:

$$S_{iF}(x) = \frac{J_{iF}(x)}{1+\tau} + E_{iF}(x) - U_i$$

$$S_{iI}(x) = J_{iI}(x) + E_{iI}(x) - U_i$$

$$S_{iS}(x) = E_{iS}(x) - U_i$$

Using the Nash-bargaining outcome for the case of employees working either in a formal or an informal firm, we have the following rules to split the total surplus:

$$\beta S_{iF(x)} = E_{iF}(x) - U_i$$

$$\beta S_{iI(x)} = E_{iI}(x) - U_i$$

That is, the wage rate must guarantee that the gain of being an employee in value terms (with respect to the outside option) $E_{ij}(x) - U_i$ is a proportion β of the total gains generated by the match (the total surplus). Note that the higher β is, the greater the gain is in terms of value for the employee. In the case of the firms, the analogous expressions are as follows (in this case, the proportion would be $(1-\beta)$:

$$(1+\tau)(1-\beta)S_{iF(x)} = J_{iF(x)}$$

$$(1-\beta)S_{iI(x)} = J_{iI(x)}$$

Using the above splitting rules and equations (A.3), (A.4), (A.6), and (A.7), we generate the following gender-specific wage equations for formal and informal employees:

$$w_{iF}(x) = \beta \frac{x}{1+\tau} + (1-\beta)\rho U_i \qquad (A.8)$$

$$w_{iI}(x) = \beta(x-c) + (1-\beta)\rho U_i \qquad (A.9)$$

The interpretation of equations (A.8) and (A.9) is the usual. The wage rate earned by the employee is a weighted average between his or her productivity and the flow value of the outside option of the workers (which is unemployment), and the weight is given by the parameter β. Note that in the case of the formal sector, the firm transfers the cost associated with the proportional payroll taxes to the worker, penalizing his or her productivity (this is reflected by the term 1). Something similar occurs in the informal sectors, with the firms transferring the flow cost of informality to employees in the form of lower wages (again penalizing their productivity by c).

Finally, it is possible the find closed-form solutions for the total surplus for all types of jobs by using the wage equations; the value functions in (A.3), (A.4), (A.6), and (A.7); and the definitions of surplus:

$$S_{iF}(x) = \frac{x-(1+\tau)\rho U_i}{(1+\tau)(\rho+\delta_{iF})}$$

$$S_{iI}(x) = \frac{x-c-\rho U_i}{(\rho+\delta_{iI})}$$

$$S_{iS}(x) = \frac{x-\rho U_i}{(\rho+\delta_{iS})}$$

A.3.3 Employment Decisions

Once productivity is realized, a match will be formed if it is acceptable for both parties in the labor relation—individuals and their potential employers. In the case of individuals, the match is acceptable if and only if the value of being an employee is higher than the value of staying in the unemployment status searching for new job opportunities (the outside option), that is, $E_{ij}(x) \geq U_i$ (i =M,W and j=F,I,S). In the same way, the match will be acceptable for the firm, either in the formal or informal sector, if and only if the value of the filled vacancy is higher than the outside option (having an empty vacancy), that is, $J_{ij}(x) \geq 0$ with $j=F,I$. It is possible to show that both $E_{ij}(x)$ and $J_{ij}(x)$ are increasing in x; therefore, the optimal decision of whether to accept or reject a match has a reservation value property. Let us define the reservation productivities (x_{ij}^*, for $i=M,W$ and $j=F,I,S$) as those productivities that make the individuals and the firms indifferent to accepting or rejecting the match and therefore satisfying the following:

$$E_{ij}\left(x_{ij}^*\right) = U_i \; and \; J_{ij}\left(x_{ij}^*\right) = 0 \Rightarrow \; S_{ij}\left(x_{ij}^*\right) = 0 \; with \; i = M, W; j = F, I,$$

In other words, the reservation productivities in all types of jobs represent the minimum required productivity to form a match. Using the value functions in (A.3), (A.4), (A.6), and (A.7), as well as the wage equations in (A.8) and (A.9) and the definition of reservation productivities, we have:

$$x_{iF}^* = (1+\tau)\rho U_i \qquad (A.10)$$
$$x_{iI}^* = \rho U_i + c \qquad (A.11)$$
$$x_{iS}^* = \rho U_i \qquad (A.12)$$

As expected, the minimum required productivity is related to the outside option flow value of the individual (unemployment) and the payroll tax and cost of informality make this productivity requirement more stringent. Evaluating the wage equations (A.8) and (A.9) at the reservation productivities, we have the reservation wage, or the minimum wage rate required by individuals to accept a match:

$$w_{iF}(x_{iF}^*) = w_{iI}(x_{iI}^*) = \rho U_i$$

Note that the reservation wages are the same for the formal and the informal sectors and are equal to the minimum acceptable earning in self-employment (which is the reservation productivity). This is a consequence of the definition of the value of unemployment in which the different types of job opportunities are substitutes.

A.3.4 Unemployment Flow Value

Finally, using the flow value of unemployment (equation A.2), the flow values of all types of employments (equations A.3 to A.5), wage rates (equation 8 and 9), and reservation productivities (equations A.10 to A.12), it can be shown that the unemployment flow value ρU_i satisfies the following Bellman equation:

$$\rho U_i = b_i + \frac{\beta\lambda_{iF}}{\rho+\delta_{iF}}\int_{(1+\tau)\rho U_i}[x-(1+\tau)\rho U_i]d\,G_{iF}(x)$$

$$+\frac{\beta\lambda_{iI}}{\rho+\delta_{iI}}\int_{\rho U_{i+c}}[x-c-\rho U_i]d\,G_{iI}(x)+\frac{\lambda_{iS}}{\rho+\delta_{iS}}\int_{\rho U_i}[x-\rho U_i]d\,G_{iS}(x),$$

$$i = M, W \qquad (A.13)$$

Note that all decisions in the equilibrium of the model are completely characterized by the unemployment flow value ρU_i.

A.3.5 Steady State

In the steady state of equilibrium, all inflows and outflows of each state are equal. The gender-specific hazard rate out of unemployment to a job type j is (with j=F,I,S); that is, the probability that an acceptable offer arrives. If there are u_i unemployed individuals, then the flow out of unemployment to a job type j is $h_{ij}u_i$. On the other hand, the hazard rate out of employment type j is δij, and therefore, the flow out of that type of job when there are e_{ij} employed individuals is $\delta_{iF}\ e_{iF}$. The three steady state conditions in this model are:

$$\lambda_{iF}[1-G_{iF}(x_{iF}^*)]u_i = \delta_{iF}e_{iF} \qquad (A.14)$$

$$\lambda_{iI}[1-G_{iI}(x_{iI}^*)]u_i = \delta_{iI}e_{iI} \qquad (A.15)$$

$$\lambda_{iS}[1-G_{iF}(x_{iS}^*)]u_i = \delta_{iS}e_{iS} \qquad (A.16)$$

Additionally, we normalized the labor force to 1, such that u_i, e_{iF}, e_{iI} and e_{iS} represent the unemployment and the employment rates in the formal sector, the informal sector, and in self-employment, respectively. That is:

$$e_{iF} + e_{iI} + e_{iS} + u_i = 1, \qquad i = M, W \tag{A.17}$$

Equations (A.14) to (A.17) represent a system of equations with four unknowns, the unemployment and employment rates. Using the definition of the hazard rate out of unemployment to an employment type j to solve the system, we have:

$$u_i = \frac{\delta_{iF}\delta_{iI}\delta_{iS}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.18}$$

$$e_{iF} = \frac{h_{iF}\delta_{iI}\delta_{iS}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.19}$$

$$e_{iI} = \frac{h_{iI}\delta_{iF}\delta_{iS}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.20}$$

$$e_{iS} = \frac{h_{iI}\delta_{iF}\delta_{iI}}{h_{iF}\delta_{iI}\delta_{iS} + h_{iI}\delta_{iF}\delta_{iS} + h_{iS}\delta_{iF}\delta_{iI} + \delta_{iF}\delta_{iI}\delta_{iS}} \tag{A.21}$$

A.4 GDP Measures

We use two measures of aggregated average production, the GDP per worker *(Y^{pw})* and the GDP per capita *(Y^{pc})*. The former divides the total production by total of workers that are currently in a job, while the latter divides the total production by the total population (including those not participating) in each country. The total GDP, in turn, is defined as the aggregated productivity by gender, and the number of workers currently employed in each type of job is used in the aggregation. The expressions that characterize Y^{pw} and Y^{pc} by gender are:

$$Y_i^{pw} = \frac{e_{iF}}{1-u_i}\int_{x_{iF}^*} x dG_{iF}(x) + \frac{e_{iI}}{1-u_i}\int_{x_{iI}^*} x dG_{iI}(x) + \frac{e_{iS}}{1-u_i}\int_{x_{iS}^*} x dG_{iS}(x)$$

$$Y_i^{pc} = (1-np_i)\left(e_{iF}\int_{x_{iF}^*} x dG_{iF}(x) + e_{iI}\int_{x_{iI}^*} x dG_{iI}(x) + e_{iS}\int_{x_{iS}^*} x dG_{iS}(x)\right)$$

Where np_i is the nonparticipation rate and $i = M, W$. The overall measures of average GDP aggregate over the gender dimension are:

$$Y_i^{pw} = Y_M^{pw} \frac{N_M^w}{N_M^w + N_W^w} + Y_W^{pw} \frac{N_W^w}{N_M^w + N_W^w}$$

$$Y_i^{pc} = Y_M^{pc} \frac{N_M}{N_M + N_W} + Y_W^{pc} \frac{N_W}{N_M + N_W}$$

Where N_i^w and N_i, with i=*M,W*, represent the number of working individuals (in either *F, I, or S*) and the total number of individuals, respectively.

B Estimation and Identification

The model is estimated by maximum likelihood methods and using supply-side data of the labor market. Data on (outgoing) unemployment duration *t*, wages in both formal (w_F) and informal (w_I) jobs, earning in self-employment activities (w_S), and individuals' labor market status were used.

B.1 Estimation

Conditional to the model, the probability of observing an individual *k* in the non-participation state is $P(z>z^*)$. Given that $z \sim Q(z)$ and $z^*=\rho U_i$, the contribution to the likelihood of non-participation information is:

$$P_i\,(k \in NP) = 1 - Q(\rho U_i) \tag{B.1}$$

To find the contribution of the unemployment duration information to this likelihood, we first define the total hazard rate out of unemployment as:

$$\begin{aligned} h_i &= \lambda_{iF}\,[1 - G_{iF}(x^*_{iF})] + \lambda_{iI}\,[1 - G_{iI}(x^*_{iI})] + \lambda_{iS}\,[1 - G_{iS}(x^*_{iS})] \\ &= h_{iF} + h_{iI} + h_{iS} \end{aligned}$$

That is, the hazard rate is the probability that a match is formed once an individual meets a potential employer of any type of job (formal or informal) or self-employment opportunity. Recall that the match is formed only if the productivity drawn from the match is greater than the corresponding reservation productivity. The hazard rate, conditional on the model, does not depend on the duration, and therefore the unemployment duration follows a negative exponential distribution with a 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 contribution of unemployment duration has to be weighted by the probability of participation ($Q(\rho U_i)$) and of being unemployed (the unemployment rate u_i). Given these considerations, the contribution of the unemployment duration information to the likelihood function is:

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

To derive the contribution of wages to the likelihood function, it is necessary to make three considerations with respect to the data on wages. First, we have information about wages but not on productivity. Second, the observed wages are those related to matches already formed, and therefore they are accepted wages. Finally, we only observe data for those individuals who are currently employed (in one of the different types of jobs). To take into account these considerations under the structure of the theoretical model, we proceed in the following way. In the first step, we map the unconditional wage-cumulative distribution from the unconditional productivity-cumulative distribution ($G_{ij}(x)$) using the wage equations for the formal and the informal sectors (in the case of those self-employed, the mapping is 1:1). In the second step, we construct the truncated version of the density wage distributions, taking into account the optimal decisions summarized in the reservation productivities (x^*_{ij}). In the final step, the truncated wage distributions are weighted by the probability of participation ($Q(\rho U_i)$) and of being employed (the employment rate in each type of job, e_{ij}). Under these considerations, wages' contribution to the likelihood function in the cases of formal and informal sectors and self-employment, respectively, are:

$$\begin{aligned} f_{e_{iF}}&\left(w_{i,k}, w_{i,k} \geq w^*_{iF}, k \in F, k \notin NP\right) \\ &= \frac{\frac{1+\tau}{\beta} g_{iF}\left(\frac{(1+\tau)(w_{i,k} - (1-\beta)\rho u_i)}{\beta}\right)}{1 - G_{iF}\big((1+\tau)\rho U_i\big)} e_{iF} Q(\rho U_i) \end{aligned} \tag{B.3}$$

$$f_{e_{iI}}\left(w_{i,k}, w_{i,k} \geq w_{iI}^{*}, k \in I, k \notin NP\right) = \frac{\frac{1}{\beta} g_{iI}\left(\frac{(w_{i,k} + \beta c - (1-\beta)\rho u_i}{\beta}\right)}{1 - G_{iI}(\rho U_i + c)} e_{iI} Q(\rho U_i) \qquad (B.4)$$

$$f_{e_{iS}}\left(w_{i,k}, w_{i,k} \geq w_{iS}^{*}, k \in S, k \notin NP\right) = \frac{g_{iI}\left(w_{i,k}\right)}{1 - G_{iS}\left(\rho U_i\right)} e_{iS} Q(\rho U_i) \qquad (B.5)$$

Putting all the contributions together, the logarithm of the joint likelihood function to be maximized is:

$$\begin{aligned} lnL(w_k, t_k, U, F, I, S, NP, \theta) &= \sum_{i=M,W} \left\{ \sum_{k \in NP} lnP_i\,(k \in NP) + \sum_{k \in U} lnf_{i,u}\left(t_{i,k}, k \in U, k \notin NP\right) \right. \\ &+ \sum_{k \in F} f_{e_{iF}}\left(w_{i,k}, w_{i,k} \geq w_{iF}^{*}, k \in F, k \notin NP\right) \\ &+ \sum_{k \in I} f_{e_{iI}}\left(w_{i,k}, w_{i,k} \geq w_{iI}^{*}, k \in I, k \notin NP\right) \\ &\left. + \sum_{k \in S} f_{e_{iS}}\left(w_{i,k}, w_{i,k} \geq w_{iS}^{*}, k \in S, k \notin NP\right) \right\} \end{aligned}$$

Where θ is the vector of primitive parameters of the model. Using the contributions defined in equations (B.1) to (B.5) and making some algebraic manipulations, the logarithm of the joint likelihood function becomes:

$$lnL(w_k, t_k, U, F, I, S, NP, \theta)$$

$$= \sum_{i=M,W} \Bigg\{ N_{NP} \ln\big(1 - Q(\rho U_i)\big) + (N_U + N_F + N_S + N_I) lnQ(\rho U_i) + N_U lnh_i$$

$$+ N_U lnu_i + N_F lne_{iF} + N_I lne_{iI} + N_S lne_{iS} - h_i \sum_{k \in U} t_{i,k}$$

$$+ \sum_{k \in F} \ln \left(\frac{\frac{1+\tau}{\beta} g_{iF}\left(\frac{(1+\tau)(w_{i,k} - (1-\beta)\rho u_i}{\beta}\right)}{1 - G_{iF}\big((1+\tau)\rho U_i\big)} \right)$$

$$+ \sum_{k \in I} \ln \left(\frac{\frac{1}{\beta} g_{iI}\left(\frac{(w_{i,k} + \beta c - (1-\beta)\rho u_i}{\beta}\right)}{1 - G_{iI}(\rho U_i + c)} \right) + \sum_{k \in S} \ln \left(\frac{g_{iI}\big(w_{i,k}\big)}{1 - G_{iS}(\rho U_i)} \right) \Bigg\}$$

Finally, we make the following parametric assumptions about the gender-specific distribution $Q_i(z)$ and the gender- and job-specific distributions $G_{ij}(x)$ $(j = F, I, S)$. For the former, we assume a negative exponential distribution with parameter γ_i, that is:

$$Q_i(z) = 1 - \exp(-\gamma_i z), \quad z > 0$$

While for the latter we assume a log normal distribution with location and scale parameters
μ_{ij} and σ_{ij}; that is, the density function of $G_{ij}(x)$ is:

$$g_{ij}(x) = \frac{1}{\sigma_{ij} x} \phi \left(\frac{\ln(x) - u_{ij}}{\sigma_{ij}} \right), \quad x > 0$$

Where $\phi(.)$ is the standard normal density function.

B.2 Identification

The identification strategy closely follows Flinn and Heckman (1982). On one hand, the identification of the mobility parameters, hazard rates, and arrival rates of the termination shocks rely on the unemployment duration information and the steady-state equilibrium conditions. On the other hand, the identification of the productivity distributions (in all types of jobs) relies on the idea of uniquely recovering the productivity and entire wage distributions from a truncated distribution with a known truncation point (the observed wage distributions). This can be done if the assumed distributions for the productivities meet what Flinn and Heckman (1982) called the recoverability condition.

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:

$$h_{iF}: \frac{N_U}{h_i} + \frac{N_U}{h_i}\frac{\partial u_i}{\partial h_{iF}} + \frac{N_F}{e_{iF}}\frac{\partial e_{iF}}{\partial h_{iF}} + \frac{N_I}{e_{iI}}\frac{\partial e_{iI}}{\partial h_{iF}} + \frac{N_S}{e_{iS}}\frac{\partial e_{iS}}{\partial h_{iF}} - \sum_{k\in U} t_{i,k} = 0 \qquad (B.6)$$

$$h_{iI}: \frac{N_U}{h_i} + \frac{N_U}{u_i}\frac{\partial u_i}{\partial h_{iI}} + \frac{N_F}{e_{iF}}\frac{\partial e_{iF}}{\partial h_{iI}} + \frac{N_I}{e_{iI}}\frac{\partial e_{iI}}{\partial h_{iI}} + \frac{N_S}{e_{iS}}\frac{\partial e_{iS}}{\partial h_{iI}} - \sum_{k\in U} t_{i,k} = 0 \qquad (B.7)$$

$$h_{iS}: \frac{N_U}{h_i} + \frac{N_U}{u_i}\frac{\partial u_i}{\partial h_{iS}} + \frac{N_F}{e_{iF}}\frac{\partial e_{iF}}{\partial h_{iS}} + \frac{N_I}{e_{iI}}\frac{\partial e_{iI}}{\partial h_{iS}} + \frac{N_S}{e_{iS}}\frac{\partial e_{iS}}{\partial h_{iI}} - \sum_{k\in U} t_{i,k} = 0 \qquad (B.8)$$

And with respect to the arrival rates of termination shocks:

$$\delta_{iF}: \frac{N_U}{u_i}\frac{\partial u_i}{\partial \delta_{iF}} + \frac{N_F}{e_{iF}}\frac{\partial e_{iF}}{\partial h_{iF}} + \frac{N_I}{e_{iI}}\frac{\partial e_{iI}}{\partial h_{iF}} + \frac{N_S}{e_{iS}}\frac{\partial e_{iS}}{\partial \delta_{iF}} = 0 \qquad (B.9)$$

$$\delta_{iI}: \frac{N_U}{u_i}\frac{\partial u_i}{\partial \delta_{iI}} + \frac{N_F}{e_{iF}}\frac{\partial e_{iF}}{\partial \delta_{iI}} + \frac{N_I}{e_{iI}}\frac{\partial e_{iI}}{\partial \delta_{iI}} + \frac{N_S}{e_{iS}}\frac{\partial e_{iS}}{\partial \delta_{iI}} = 0 \qquad (B.10)$$

$$\delta_{iS}: \frac{N_U}{u_i}\frac{\partial u_i}{\partial \delta_{iS}} + \frac{N_F}{e_{iF}}\frac{\partial e_{iF}}{\partial \delta_{iS}} + \frac{N_I}{e_{iI}}\frac{\partial e_{iI}}{\partial \delta_{iS}} + \frac{N_S}{e_{iS}}\frac{\partial e_{iS}}{\partial \delta_{iS}} = 0 \qquad (B.11)$$

Where $\frac{\partial X}{\partial Y}$ is the partial derivative of the steady state condition X (u_i, e_{iF}, e_{iI}, and e_{iS} in equations A.18 to A.21) with respect to the parameter Y (the hazard rates and the termination shock Poisson rates). Note that equations (B.6) to (B.11) represent a nonlinear system of six equations with six unknowns for each gender type (h_{iF}, h_{iI} h_{iS}, δ_{iF}, δ_{iF}, and δ_{iF}). These parameters are identified if the solution of this system of equations is unique. Thus, in the context of nonlinear systems of equations, there is a possibility of multiple solutions. To overcome this possibility, we follow Bobba et al. (2017) and restrict the solutions to those that satisfy $\lambda_{iF} = \lambda_{iI}$ and $\delta_{iF} = \delta_{iI}$, that is, for waged jobs, formal and informal, the arrival rates of meetings and terminations are the same.

With respect to the productivity distributions, we assume, as discussed in the previous subsection, that they take a lognormal form. As discussed by Eckstein and van den Berg (2007), this parametrization meets the recoverability condition and belongs to a log location-scale family; therefore, the location and the scale of the original distribution should be identified from the location and the scale of the truncated distribution. To see this in the context of the distribution of the different types of jobs, we re-parametrize the observed wage distribution for the case of formal jobs in the following way:

$$\frac{\frac{1+\tau}{\beta} g_{iF}\left(\frac{(1+\tau)(w_{i,k}-(1-\beta)\rho u_i}{\beta}\right)}{1-G_{iF}\big((1+\tau)\rho U_i\big)} = \frac{\frac{1}{w_{i,k}\sigma_{iF,0}} \emptyset_{iF}\left(\frac{\ln(w_{i,k}-\mu_{iF,0}}{\sigma_{iF,0}}\right)}{1-\Phi_{iF}\left(\frac{\ln(\rho U_i)-\mu_{iF,0}}{\sigma_{iF,0}}\right)}$$

Where:

$$\mu_{iF,0} = (1-\beta)\rho U_i + \frac{\beta}{(1+\tau)}\mu_{iF} \qquad (B.12)$$

$$\sigma_{iF,0} = \frac{\beta}{(1+\tau)}\sigma_{iF} \qquad (B.13)$$

That is, $\mu_{iF,0}$ and $\sigma_{iF,0}$ are the mean (location) and standard deviation (scale) of the observed wage distribution, respectively, and μ_{iF} and σ_{iF} are the mean (location) and standard deviation (scale) of the productivity distribution. From (B.12) and (B.13), it follows immediately that if ρU_i, β and τ are known, then μ_{iF} and σ_{iF} are uniquely identified from the data on wages in the formal sector. The parameters β and τ are not identified, and therefore they are just set. We set β at 0.5 for all countries, while in the case of τ, we use information about the payroll contributions of each country. Using the same re-parametrization for the observed wage distribution for the case of informal jobs, we have:

$$\frac{\frac{1}{\beta}g_{iI}\left(\frac{(w_{i,k}+\beta c-(1-\beta)\rho U_i)}{\beta}\right)}{1-G_{iI}(\rho U_i+c)}=\frac{\frac{1}{w_{i,k}\sigma_{iI,0}}\emptyset_{iI}\left(\frac{\ln(w_{i,k}-\mu_{iI,0})}{\sigma_{iI,0}}\right)}{1-\Phi_{iI}\left(\frac{\ln(\rho U_i)-\mu_{iI,0}}{\sigma_{iI,0}}\right)}$$

Where:

$$\mu_{iI,0}=(1-\beta)\rho U_i+\beta(\mu_{iI}-c) \qquad (B.14)$$

$$\sigma_{iI,0}=\beta\sigma_{iI} \qquad (B.15)$$

In this case, μ_{iI} and σ_{iI} 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 identify the productivity distribution in the informal sector. 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 c across countries.

Finally, the re-parametrization of observed wage distribution for the case of self-employed workers gives:

$$\frac{g_{iI}(w_{i,k})}{1-G_{iS}(\rho U_i)}=\frac{\frac{1}{w_{i,k}\sigma_{iS,0}}\emptyset_{iS}\left(\frac{\ln(w_{i,k}-\mu_{iS,0})}{\sigma_{iS,0}}\right)}{1-\Phi_{iS}\left(\frac{\ln(\rho U_i)-\mu_{iS,0}}{\sigma_{iS,0}}\right)}$$

Where:

$$\mu_{iS,0}=\mu_{iS} \qquad (B.16)$$

$$\sigma_{iS,0}=\sigma_{iS} \qquad (B.17)$$

Given that there is no bargaining involved in self-employment, the location and scale of the productivity distribution in equations (B.16) and (B.18) are identified one to one from their counterparts in the observed wage distribution provided that ρU_i is known.

Flinn and Heckman (1982) showed that the minimum observed wage is a strongly consistent nonparametric estimator of the reservation wage. This estimator is typically used in the literature to estimate ρU_i. However, because the model in this paper indicates that $w_{iF}(x^*_{iF}) = w_{iI}(x^*_{iI}) = x^*_{iI} = \rho U_i$, the Flinn and Heckman (1982) estimator implies that $\min w^0_{iF} = \min w^0_{iI} = \min w^0_{iS} = \rho U_i$ 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 alters 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 assume that the measurement error E is multiplicative, and, therefore, the observed wages can be expressed as $w^o = w \times E$. The assumptions we make about the measurement error are threefold:

(1) the measurement error is gender specific;

(2) we use a lognormal distribution for the measurement error:

$v_i(\epsilon) = \frac{1}{\epsilon \sigma_{\epsilon_i}} \phi\left(\frac{ln\epsilon - \mu_{\epsilon_i}}{\sigma_{\epsilon_i}}\right)$, where $\phi(.)$ is the standard normal density function, i=M, W;

(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 $E[E|w] = 1$.

All these assumptions together imply that the parameters μ_{ϵ_i} and σ_{ϵ_i} satisfy $\sigma_{\epsilon_i} = \sqrt{-2\mu_{\epsilon_i}}$ with i=M,W, 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:

$$f^0_{e_{iF}}\left(w^0_{i,k}\right) = \int_{\rho U_i} \frac{1}{w_i} v_i\left(\frac{w^0_{i,k}}{w_i}\right) f_{e_{iF}}(w_i, w_i \geq \rho U_i, k \in F, k \notin NP) dw_i \qquad (B.18)$$

$$f^0_{e_{iI}}\left(w^0_{i,k}\right) = \int_{\rho U_i} \frac{1}{w_i} v_i\left(\frac{w^0_{i,k}}{w_i}\right) f_{e_{iI}}(w_i, w_i \geq w^*_{iI}, k \in F, k \notin NP) dw_i \qquad (B.19)$$

$$f^0_{e_{iS}}\left(w^0_{i,k}\right) = \int_{\rho U_i} \frac{1}{w_i} v_i\left(\frac{w^0_{i,k}}{w_i}\right) f_{e_{iS}}(w_i, w_i \geq w^*_{iS}, k \in S, k \notin NP) dw_i \qquad (B.20)$$

Finally, to identify the parameter γ_i in $Q_i(z)$, the assumed distribution must 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:

$$\gamma_i = \frac{ln\left(\frac{N_i}{N_{i,NP}}\right)}{\rho U_i}$$

Where N_i is the total number of individuals and $N_{i,NP}$ is the number of individuals who are not participating in the labor market by gender. To analyze the influence of the presence of children in the household on the participation rates (in particular in the γ_i parameter), we divided nonparticipating 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 nonparticipants (other). It can be shown that if $Pr[NP \cap k5] + Pr[NP \cap k13] + Pr[NP \cap other] = Pr[NP]$, the estimator of the parameter γ by group is:

$$\gamma_i^g = \frac{ln\left(\frac{N_i^g}{N_{i,NP}^g}\right)}{\rho U_i}$$

Where N_i^g is the total numbers of individuals in the group g and $N_{i,NP}^g$ is the number of individuals who are not participating in the group g by gender.

C Complete Estimation Results

Tables C.4, C.7, C.10, and C.13 report the estimated structural parameters of the model for each country, gender, and education group. Tables C.5, C.8, C.11, and C.14 report the implications for the labor market dynamics and the distribution across labor market states. As mentioned in the main text, we perform two policy experiments. Tables C.6, C.9, C.12, and C.15 report the impact of the policy experiments on a variety of labor market outcomes along with the same outcomes reported at benchmark. Finally, Tables C.16, C.17, and C.18 report aggregated results on participation rates and GDP per capita; the figures presented in the main text are based in these tables.

Table C.1: Argentina - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	0.2010	0.1481	1.7531	1.4020	1.8737	1.6045
	(0.0407)	(0.0955)	(0.0545)	(0.0469)	(0.0994)	(0.0566)
λ_F	0.1290	0.1270	0.2149	0.1825	0.2095	0.2009
	(0.0068)	(0.0060)	(0.0117)	(0.0056)	(0.0057)	(0.0060)
λ_S	0.0991	0.0492	0.1434	0.1192	0.0855	0.0496
	(0.0149)	(0.0069)	(0.0164)	(0.2133)	(0.0043)	(0.0022)
δ_F	0.0235	0.0298	0.0166	0.0286	0.0115	0.0147
	(0.0011)	(0.0014)	(0.0009)	(0.0009)	(0.0003)	(0.0004)
δ_S	0.0194	0.0212	0.0106	0.0056	0.0100	0.0114
	(0.0011)	(0.0030)	(0.0011)	(0.0019)	(0.0003)	(0.0005)
μ_F	2.5652	2.3973	2.5337	2.4788	2.8459	2.8579
	(0.0109)	(0.0164)	(0.0106)	(0.0168)	(0.0115)	(0.0110)
σ_F	0.0055	0.0056	0.0023	0.0044	0.0015	0.0009
	(0.0014)	(0.0118)	(0.0015)	(0.0015)	(0.0005)	(0.0006)
μ_I	1.6267	1.6492	0.2905	0.7025	-0.8285	-0.7050
	(0.0096)	(0.0199)	(0.0543)	(0.0203)	(0.1254)	(0.0513)
σ_I	0.2555	0.3702	0.8894	0.8820	1.6094	1.6250
	(0.0228)	(0.0172)	(0.0568)	(0.0372)	(0.0864)	(0.0342)
μ_S	0.9628	0.6250	0.3670	-1.1566	1.1756	1.0534
	(0.1563)	(0.0325)	(0.2372)	(1.3264)	(0.0894)	(0.1054)
σ_S	0.5374	0.7032	0.8134	1.2801	0.7668	0.8915
	(0.0491)	(0.0196)	(0.0784)	(0.2740)	(0.0433)	(0.0536)
σ_{ME}	0.4533	0.4495	0.4626	0.4834	0.4778	0.4574
	(0.0055)	(0.0095)	(0.0057)	(0.0077)	(0.0061)	(0.0054)
γ	11.5668	4.4577	1.7097	0.6790	1.3644	0.9826
γ_{k5}	-	3.6072	-	0.5685	-	0.8183
γ_{k13}	-	4.7808	-	0.7131	-	1.0216
γ_{other}	-	5.3368	-	0.7787	-	1.0859
b	-16.2883	-4.6048	-14.1671	-10.3582	-2.3621	-1.6530
c	0.4717	0.4717	0.5350	0.5350	0.4710	0.4710
Likelihood	-21,279	-11,291	-13,751	-9,427	-13,581	-17,417
N	7534	7637	4587	4759	4318	6503

Note: Bootstrap standard errors (based on 25 replications) in parentheses. Nonestimated parameters: $\beta = 0.5$, $\tau = 0.48$, and $\rho = 0.062$.

Table C.2: 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	0.332	0.292	0.879	0.306	0.276	0.902
$h_{u \to e_F}$									
Model	0.129	0.127	0.984	0.215	0.182	0.849	0.209	0.201	0.959
$h_{u \to e_I}$									
Model	0.129	0.127	0.984	0.059	0.095	1.614	0.031	0.038	1.221
$h_{u \to e_S}$									
Model	0.099	0.049	0.497	0.058	0.014	0.249	0.065	0.037	0.565
u									
Data	0.059	0.084	1.432	0.044	0.075	1.719	0.035	0.049	1.390
Model	0.058	0.084	1.444	0.044	0.075	1.730	0.035	0.049	1.386
e_F									
Data	0.382	0.290	0.760	0.564	0.488	0.865	0.641	0.670	1.044
Model	0.321	0.360	1.119	0.563	0.481	0.854	0.640	0.668	1.043
e_I									
Data	0.261	0.429	1.645	0.153	0.244	1.597	0.094	0.124	1.321
Model	0.321	0.360	1.119	0.154	0.249	1.623	0.095	0.126	1.327
e_S									
Data	0.299	0.197	0.659	0.239	0.193	0.808	0.229	0.157	0.686
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 C.3: Argentina- Policy Experiments

		Benchmark		P. Exp. No. 1		P. Exp. No. 2	
	M	W	W/M	W	W/M	W	W/M
Primary							
u	0.058	0.084	1.444	0.084	1.444	0.086	1.47
e_F	0.321	0.36	1.119	0.36	1.119	0.366	1.139
e_I	0.321	0.36	1.119	0.36	1.119	0.366	1.139
e_S	0.299	0.196	0.657	0.196	0.657	0.182	0.609
np	0.098	0.517	5.282	0.422	4.312	0.019	0.198
h_u	0.357	0.303	0.849	0.303	0.849	0.299	0.837
GDP_W	7.189	7.035	0.979	7.032	0.978	7.862	1.094
GDP_C	6.107	3.113	0.51	3.722	0.61	7.047	1.154
$E[w \mid e_F]$	4.524	3.769	0.833	3.788	0.837	4.518	0.999
$E[w \mid e_I]$	2.499	2.64	1.057	2.607	1.043	3.29	1.317
$E[w \mid e_S]$	3.034	2.434	0.802	2.418	0.797	2.797	0.922
Res. W.	0.201	0.148	0.737	0.148	0.737	0.885	4.402
Secondary							
u	0.044	0.075	1.73	0.075	1.73	0.079	1.815
e_F	0.563	0.481	0.854	0.481	0.854	0.504	0.895
e_I	0.154	0.249	1.623	0.249	1.623	0.252	1.637
e_S	0.239	0.194	0.811	0.194	0.811	0.165	0.688
np	0.05	0.386	7.732	0.297	5.947	0.294	5.89
h_u	0.332	0.292	0.879	0.292	0.879	0.285	0.86
GDP_W	9.025	8.151	0.903	8.166	0.905	9.298	1.03
GDP_C	8.201	4.627	0.564	5.308	0.647	6.044	0.737
$E[w \mid e_F]$	5.161	4.76	0.922	4.7	0.911	5.331	1.033
$E[w \mid e_I]$	2.841	2.81	0.989	2.825	0.994	3.271	1.151
$E[w \mid e_S]$	3.524	3.185	0.904	3.226	0.915	3.795	1.077
Res. W.	1.753	1.402	0.8	1.402	0.8	1.803	1.028
Tertiary							
u	0.035	0.049	1.386	0.049	1.386	0.05	1.43
e_F	0.64	0.668	1.043	0.668	1.043	0.689	1.076
e_I	0.095	0.126	1.327	0.126	1.327	0.113	1.194
e_S	0.229	0.157	0.686	0.157	0.686	0.147	0.642
np	0.078	0.207	2.664	0.15	1.931	0.107	1.374
h_u	0.306	0.276	0.902	0.276	0.902	0.267	0.875
GDP_W	13.462	14.111	1.048	14.129	1.049	15.968	1.186
GDP_C	11.98	10.647	0.889	11.425	0.954	13.548	1.131
$E[w \mid e_F]$	6.749	6.7	0.993	6.683	0.99	7.632	1.131
$E[w \mid e_I]$	4.565	4.287	0.939	4.507	0.987	5.518	1.209
$E[w \mid e_S]$	5.284	5.432	1.028	5.272	0.998	6.208	1.175
Res. W.	1.874	1.604	0.856	1.604	0.856	2.279	1.216

Table C.4: Chile - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	1.1619	0.1351	1.6535	0.9071	3.2590	2.1330
	(0.0357)	(0.0118)	(0.0366)	(0.0470)	(0.5817)	(0.0939)
λ_F	0.2187	0.1394	0.2760	0.2431	0.2084	0.2457
	(0.0134)	(0.0104)	(0.0176)	(0.0264)	(0.0175)	(0.0150)
λ_S	0.2079	0.2016	0.4536	0.2617	0.1855	0.2000
	(0.0136)	(0.0099)	(0.1395)	(0.0151)	(0.0341)	(0.0185)
δ_F	0.0330	0.0697	0.0277	0.0349	0.0190	0.0213
	(0.0020)	(0.0052)	(0.0018)	(0.0043)	(0.0016)	(0.0013)
δ_S	0.0396	0.0836	0.0186	0.0449	0.0314	0.0456
	(0.0016)	(0.0041)	(0.0050)	(0.0038)	(0.0051)	(0.0042)
μ_F	1.6253	1.5930	1.7619	1.6358	2.5841	2.3593
	(0.0089)	(0.0057)	(0.0077)	(0.0111)	(0.0747)	(0.0131)
σ_F	0.0060	0.0829	0.0050	0.0042	0.1404	0.0109
	(0.0016)	(0.0097)	(0.0029)	(0.0010)	(0.3038)	(0.0028)
μ_I	-1.0817	1.3222	-1.2449	-1.6818	-1.1511	-2.3261
	(0.0833)	(0.0139)	(0.1205)	(0.3976)	(0.7495)	(0.1887)
σ_I	1.4102	0.4296	1.3240	1.5077	1.5287	2.0542
	(0.0597)	(0.0352)	(0.0734)	(0.2125)	(0.3472)	(0.1016)
μ_S	0.4620	0.5272	-0.9682	-0.4041	1.0003	0.4949
	(0.0607)	(0.0215)	(0.4858)	(0.1258)	(0.2478)	(0.2148)
σ_S	0.7043	0.8061	1.2050	1.2339	0.9905	1.1606
	(0.0247)	(0.0208)	(0.1031)	(0.0700)	(0.0734)	(0.0748)
σ_{ME}	0.3942	0.2839	0.4271	0.3714	0.6752	0.5976
	(0.0040)	(0.0062)	(0.0033)	(0.0050)	(0.1305)	(0.0038)
γ	1.6296	3.3170	1.7197	0.9810	0.7113	0.7077
$\gamma k5$	-	3.0758	-	0.8302	-	0.6118
$\gamma k13$	-	3.5538	-	1.0149	-	0.7252
$\gamma other$	-	3.3422	-	1.1237	-	0.7782
b	-5.2273	-7.1409	-5.263	-6.1255	-12.5320	-12.7444
c	0.2809	0.2809	0.3425	0.3425	0.5119	0.5119
Likelihood	-28044	-15330	-38209	-26514	-42153	-38439
N	12500	15929	15321	18270	12978	15388

Note: Bootstrap standard errors (based on 25 replications) in parentheses. Nonestimated parameters: $\beta = 0.5$, $\tau = 0.20$, and $\rho = 0.067$.

Table C.5: 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	0.219	0.139	0.637	0.276	0.243	0.881	0.208	0.246	1.179
$h_{u \to e_I}$									
Model	0.033	0.139	4.187	0.020	0.025	1.266	0.011	0.013	1.217
$h_{u \to e_S}$									
Model	0.140	0.201	1.444	0.050	0.105	2.088	0.079	0.082	1.036
u									
Data	0.082	0.135	1.641	0.069	0.091	1.311	0.066	0.067	1.006
Model	0.082	0.135	1.642	0.069	0.091	1.306	0.066	0.067	1.006
e_F									
Data	0.547	0.470	0.859	0.693	0.655	0.946	0.727	0.771	1.060
Model	0.545	0.270	0.495	0.692	0.632	0.912	0.727	0.771	1.060
e_I									
Data	0.081	0.070	0.860	0.050	0.049	0.995	0.038	0.041	1.088
Model	0.083	0.270	3.252	0.050	0.065	1.311	0.038	0.042	1.094
e_S									
Data	0.289	0.325	1.124	0.188	0.205	1.087	0.168	0.120	0.716
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
Model0.151	0.639	4.243	0.058	0.411	7.055	0.098	0.221	2.24	

Table C.6: Chile - Policy Experiments

		Benchmark		P. Exp. No. 1		P. Exp. No. 2	
	M	W	W/M	W	W/M	W	W/M
Primary							
u	0.135	1.642	0.135	1.642	0.135	1.648	
e_F	0.545	0.27	0.495	0.27	0.495	0.271	0.497
e_I	0.083	0.27	3.252	0.27	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	0.48	1.226	0.48	1.226	0.478	1.221
GDP_W	4.206	3.715	0.883	3.7	0.88	4.102	0.975
GDP_C	3.279	1.161	0.354	1.375	0.419	2.47	0.753
$E[w\|e_F]$	2.698	2.121	0.786	2.126	0.788	2.441	0.905
$E[w\|e_I]$	2.346	1.993	0.85	1.976	0.842	2.307	0.984
$E[w\|e_S]$	2.666	2.337	0.877	2.346	0.88	2.641	0.99
Res. W.	1.162	0.135	0.116	0.135	0.116	0.359	0.309
Secondary							
u	0.069	0.091	1.306	0.091	1.306	0.092	1.318
e_F	0.692	0.632	0.912	0.632	0.912	0.637	0.921
e_I	0.05	0.065	1.311	0.065	1.311	0.063	1.269
e_S	0.188	0.213	1.129	0.213	1.129	0.208	1.104
np	0.058	0.411	7.055	0.322	5.529	0.34	5.848
h_u	0.346	0.373	1.078	0.373	1.078	0.369	1.066
GDP_W	5.265	4.489	0.853	4.509	0.856	4.975	0.945
GDP_C	4.614	2.405	0.521	2.78	0.603	2.981	0.646
$E[w\|e_F]$	3.254	2.594	0.797	2.584	0.794	2.906	0.893
$E[w\|e_I]$	2.913	1.885	0.647	1.934	0.664	2.18	0.748
$E[w\|e_S]$	3.449	2.956	0.857	3.037	0.88	3.295	0.955
Res. W.	1.653	0.907	0.549	0.907	0.549	1.098	0.664
Tertiary							
u	0.066	0.067	1.006	0.067	1.006	0.068	1.017
e_F	0.727	0.771	1.06	0.771	1.06	0.78	1.072
e_I	0.038	0.042	1.094	0.042	1.094	0.039	1.027
e_S	0.168	0.12	0.716	0.12	0.716	0.114	0.676
np	0.098	0.221	2.244	0.159	1.612	0.15	1.523
h_u	0.299	0.341	1.142	0.341	1.142	0.335	1.121
GDP_W	12.261	10.059	0.82	10.062	0.821	11.123	0.907
GDP_C	10.319	7.312	0.709	7.899	0.765	8.815	0.854
$E[w\|e_F]$	7.21	5.481	0.76	5.489	0.761	6.21	0.861
$E[w\|e_I]$	6.28	5.542	0.882	7.108	1.132	6.883	1.096
$E[w\|e_S]$	8.037	6.569	0.817	6.332	0.788	7.192	0.895
Res. W.	3.259	2.133	0.654	2.133	0.654	2.681	0.823

Table C.7: Colombia - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	0.0950	0.0209	0.7971	0.3286	0.9019	0.8454
	(0.0044)	(0.1501)	(0.0149)	(0.0428)	(0.0198)	(0.0215)
λ_F	0.0746	0.0379	0.1437	0.0757	0.0997	0.0875
	(0.0014)	(0.0160)	(0.0110)	(0.0073)	(0.0036)	(0.0029)
λ_S	0.1727	0.1440	0.4241	0.2742	0.1105	0.0833
	(0.0034)	(0.0346)	(0.1671)	(0.0292)	(0.0048)	(0.0019)
δ_F	0.0291	0.0391	0.0227	0.0457	0.0183	0.0240
	(0.0000)	(0.0165)	(0.0017)	(0.0046)	(0.0007)	(0.0008)
δ_S	0.0190	0.0284	0.0117	0.0159	0.0240	0.0374
	(0.0001)	(0.0069)	(0.0019)	(0.0015)	(0.0012)	(0.0009)
μ_F	1.1613	1.1683	1.0160	1.1223	1.7155	1.8122
	(0.0086)	(0.0209)	(0.0090)	(0.0106)	(0.0207)	(0.0091)
σ_F	0.2402	0.0045	0.0018	0.0006	0.6252	0.0167
	(0.0085)	(0.0038)	(0.0029)	(0.0007)	(0.0271)	(0.0042)
μ_I	0.7369	0.5953	-0.5990	0.5507	-1.3505	-1.3142
	(0.0102)	(0.0613)	(0.0390)	(0.0284)	(0.0797)	(0.0846)
σ_I	0.3455	0.0083	0.7296	0.2081	1.1012	1.0515
	(0.0083)	(0.0705)	(0.0352)	(0.1011)	(0.0531)	(0.0524)
μ_S	-0.0266	-0.3949	-1.0855	-2.5155	0.4301	0.5819
	(0.0082)	(0.0264)	(0.3267)	(0.2531)	(0.0670)	(0.0323)
σ_S	0.5487	0.6568	0.8868	1.6566	0.9237	0.7441
	(0.0057)	(0.0957)	(0.0700)	(0.1842)	(0.0334)	(0.0254)
σ_{ME}	0.1521	0.3836	0.3441	0.3380	0.4046	0.6196
	(0.0069)	(0.0823)	(0.0045)	(0.0335)	(0.0163)	(0.0039)
γ	27.1017	38.1053	3.8753	3.5139	3.0554	2.1419
γ_{k5}	-	35.6767	-	3.1030	-	1.8271
γ_{k13}	-	40.3819	-	3.8456	-	2.2715
γ_{other}	-	38.5067	-	3.6471	-	2.3540
b	-4.7300	-2.4169	0.002	-0.9108	-5.2873	-3.4859
c	0.1371	0.1371	0.1520	0.1520	0.2139	0.2139
Likelihood	-17037	-12564	-17264	-16544	-25763	-33577
N	9947	12060	8956	10581	9171	13252

Note: Bootstrap standard errors (based on 25 replications) in parentheses. Nonestimated parameters: β = 0.5, τ = 0.31, and ρ = 0.053.

Table C.8: 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	0.038	0.508	0.144	0.076	0.527	0.099	0.087	0.883
$h_{u \to e_I}$									
Model	0.075	0.038	0.508	0.033	0.076	2.323	0.009	0.008	0.912
$h_{u \to e_S}$									
Model	0.173	0.144	0.834	0.071	0.054	0.771	0.079	0.070	0.885
u									
Data	0.066	0.125	1.890	0.068	0.136	2.012	0.098	0.145	1.486
Model	0.066	0.125	1.898	0.068	0.129	1.913	0.098	0.145	1.486
e_F									
Data	0.194	0.101	0.520	0.428	0.310	0.725	0.530	0.531	1.002
Model	0.168	0.121	0.718	0.427	0.214	0.501	0.530	0.531	1.002
e_I									
Data	0.143	0.141	0.988	0.096	0.129	1.342	0.049	0.051	1.032
Model	0.168	0.121	0.718	0.097	0.214	2.209	0.049	0.051	1.034
e_S									
Data	0.597	0.633	1.060	0.409	0.426	1.041	0.323	0.273	0.845
Model	0.597	0.633	1.060	0.409	0.443	1.084	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 C.9: Colombia - Policy Experiments

	Benchmark			P. Exp. No. 1		P. Exp. No. 2	
	M	W	W/M	W	W/M	W	W/M
Primary							
u	0.066	0.125	1.898	0.125	1.898	0.125	1.899
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	1.06	0.633	1.06	0.633	1.06
np	0.076	0.45	5.907	0.369	4.836	0.024	0.309
h_u	0.322	0.22	0.683	0.22	0.683	0.22	0.683
GDP_W	1.714	1.301	0.759	1.302	0.759	1.432	0.835
GDP_C	1.48	0.626	0.423	0.719	0.486	1.223	0.827
$E[w\|e_F]$	1.3	1.242	0.955	1.248	0.96	1.379	1.061
$E[w\|e_I]$	1.087	0.84	0.772	0.843	0.775	0.978	0.9
$E[w\|e_S]$	1.131	0.839	0.741	0.835	0.738	0.925	0.818
Res. W.	0.095	0.021	0.221	0.021	0.221	0.098	1.036
Secondary							
u	0.068	0.129	1.913	0.129	1.913	0.132	1.95
e_F	0.427	0.214	0.501	0.214	0.501	0.218	0.511
e_I	0.097	0.214	2.209	0.214	2.209	0.218	2.251
e_S	0.409	0.443	1.084	0.443	1.084	0.432	1.058
np	0.046	0.315	6.919	0.238	5.232	0.249	5.461
h_u	0.247	0.206	0.834	0.206	0.834	0.204	0.824
GDP_W	2.041	1.821	0.892	1.843	0.903	2.048	1.003
GDP_C	1.817	1.086	0.598	1.222	0.673	1.336	0.735
$E[w\|e_F]$	1.452	1.336	0.92	1.331	0.917	1.488	1.025
$E[w\|e_I]$	1.105	0.974	0.882	0.972	0.88	1.094	0.99
$E[w\|e_S]$	1.405	1.23	0.875	1.29	0.918	1.423	1.012
Res. W.	0.797	0.329	0.412	0.328	0.412	0.396	0.497
Tertiary							
u	0.098	0.145	1.486	0.145	1.486	0.147	1.506
e_F	0.53	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	0.163	0.872
GDP_W	5.2	4.786	0.92	4.782	0.92	5.311	1.021
GDP_C	4.393	3.421	0.779	3.636	0.828	4.06	0.924
$E[w\|e_F]$	3.045	2.76	0.907	2.758	0.906	3.114	1.023
$E[w\|e_I]$	1.392	1.288	0.925	1.295	0.93	1.55	1.113
$E[w\|e_S]$	3.066	2.728	0.89	2.691	0.878	2.952	0.963
Res. W.	0.902	0.845	0.937	0.845	0.937	1.059	1.174

Table C.10: Mexico - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	0.0779	0.0866	0.9945	0.6806	1.4056	1.1648
	(0.0342)	(0.0048)	(0.0093)	(0.0079)	(0.0704)	(0.0306)
λ_F	0.2604	0.1790	0.2614	0.2914	0.2168	0.2750
	(0.0247)	(0.0166)	(0.0100)	(0.0206)	(0.0093)	(0.0198)
λ_S	0.2824	0.3073	0.3034	0.5872	0.1744	0.4172
	(0.0138)	(0.0236)	(0.0249)	(0.0992)	(0.0141)	(0.4063)
δ_F	0.0290	0.0291	0.0236	0.0336	0.0240	0.0246
	(0.0028)	(0.0027)	(0.0009)	(0.0024)	(0.0010)	(0.0018)
δ_S	0.0384	0.0248	0.0247	0.0179	0.0442	0.0242
	(0.0019)	(0.0019)	(0.0020)	(0.0022)	(0.0028)	(0.0069)
μ_F	1.2960	1.0563	1.0638	1.0281	1.8190	1.8075
	(0.0208)	(0.0228)	(0.0069)	(0.0092)	(0.0137)	(0.0089)
σ_F	0.1146	0.1178	0.0034	0.0189	0.0180	0.0228
	(0.1174)	(0.0869)	(0.0009)	(0.0041)	(0.1276)	(0.0094)
μ_I	0.9046	0.6911	0.1910	-0.1791	-0.3012	-0.6902
	(0.0157)	(0.0215)	(0.0067)	(0.0089)	(0.1209)	(0.0515)
σ_I	0.1622	0.3504	0.4401	0.7646	0.9147	1.1594
	(0.0893)	(0.0451)	(0.0153)	(0.0121)	(0.0911)	(0.0369)
μ_S	0.3908	-0.1133	-0.3031	-1.6270	0.5568	-1.2754
	(0.0283)	(0.0278)	(0.1370)	(0.2744)	(0.1216)	(0.8081)
σ_S	0.5210	0.7612	0.8395	1.3079	0.7455	1.2789
	(0.0487)	(0.0291)	(0.0489)	(0.0728)	(0.0540)	(0.1591)
σ_{ME}	0.3716	0.3206	0.4322	0.4432	0.5736	0.5552
	(0.1504)	(0.1041)	(0.0028)	(0.0038)	(0.0233)	(0.0045)
γ	25.1856	4.2741	2.6676	0.8351	1.6379	0.8487
γ_{k5}	-	3.7244	-	0.6902	-	0.7738
γ_{k13}	-	4.6411	-	0.8890	-	0.8623
γ_{other}	-	4.5132	-	0.9857	-	0.8958
b	-13.7186	-9.0288	-3.464	-4.5471	-6.6944	-8.2247
c	0.1495	0.1495	0.1669	0.1669	0.2116	0.2116
Likelihood	-18023	-9219	-53030	-30738	-31751	-28936
N	10048	15100	26008	32155	12385	17086

Note: Bootstrap standard errors (based on 25 replications) in parentheses. Nonestimated parameters: β = 0.5, τ = 0.33, and ρ = 0.056.

Table C.11: 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	0.803	0.665	0.828	0.511	0.536	1.047	0.366	0.383	1.045
$h_{u \to e_F}$									
Model	0.260	0.179	0.687	0.261	0.291	1.115	0.217	0.275	1.269
$h_{u \to e_I}$									
Model	0.260	0.179	0.687	0.140	0.144	1.023	0.043	0.053	1.240
$h_{u \to e_S}$									
Model	0.282	0.307	1.087	0.110	0.100	0.916	0.107	0.055	0.515
u									
Data	0.038	0.039	1.026	0.045	0.051	1.149	0.070	0.060	0.860
Model	0.038	0.039	1.025	0.045	0.051	1.149	0.070	0.060	0.860
e_F									
Data	0.279	0.228	0.815	0.493	0.447	0.906	0.635	0.674	1.061
Model	0.341	0.240	0.703	0.493	0.443	0.899	0.635	0.673	1.060
e_I									
Data	0.403	0.252	0.625	0.265	0.215	0.810	0.125	0.129	1.032
Model	0.341	0.240	0.703	0.265	0.219	0.825	0.125	0.129	1.036
e_S									
Data	0.280	0.481	1.721	0.197	0.287	1.455	0.170	0.137	0.807
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 C.12: Mexico - Policy Experiments

	Benchmark			P. Exp. No. 1		P. Exp. No. 2	
	M	W	W/M	W	W/M	W	W/M
Primary							
u	0.038	0.039	1.025	0.039	1.025	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	0.803	0.665	0.828	0.665	0.828	0.661	0.822
GDP_W	2.683	1.858	0.693	1.850	0.690	2.052	0.765
GDP_C	2.218	0.552	0.249	0.671	0.302	1.209	0.545
$E[w\|e_F]$	1.420	1.126	0.793	1.130	0.796	1.305	0.919
$E[w\|e_I]$	1.216	1.032	0.849	1.031	0.848	1.202	0.989
$E[w\|e_S]$	1.700	1.203	0.708	1.194	0.703	1.338	0.787
Res. W.	0.078	0.087	1.111	0.087	1.111	0.222	2.853
Secondary							
u	0.045	0.051	1.149	0.051	1.149	0.052	1.177
e_F	0.493	0.443	0.899	0.443	0.899	0.454	0.921
e_I	0.265	0.219	0.825	0.219	0.825	0.221	0.834
e_S	0.197	0.287	1.455	0.287	1.455	0.272	1.381
np	0.07	0.566	8.042	0.475	6.75	0.507	7.197
h_u	0.511	0.536	1.047	0.536	1.047	0.526	1.029
GDP_W	2.387	2.229	0.934	2.242	0.939	2.475	1.037
GDP_C	2.121	0.917	0.432	1.116	0.526	1.157	0.545
$E[w\|e_F]$	1.587	1.39	0.876	1.392	0.877	1.554	0.979
$E[w\|e_I]$	1.294	1.136	0.878	1.136	0.878	1.28	0.989
$E[w\|e_S]$	1.968	1.71	0.869	1.745	0.887	1.923	0.977
Res. W.	0.995	0.681	0.684	0.681	0.684	0.814	0.818
Tertiary							
u	0.07	0.06	0.86	0.06	0.86	0.062	0.888
e_F	0.635	0.673	1.06	0.673	1.06	0.695	1.095
e_I	0.125	0.129	1.036	0.129	1.036	0.121	0.969
e_S	0.17	0.137	0.807	0.137	0.807	0.122	0.715
np	0.1	0.372	3.72	0.299	2.985	0.293	2.927
h_u	0.366	0.383	1.045	0.383	1.045	0.37	1.01
GDP_W	5.194	5.193	1	5.196	1	5.824	1.121
GDP_C	4.346	3.064	0.705	3.425	0.788	3.862	0.889
$E[w\|e_F]$	3.019	2.874	0.952	2.858	0.947	3.249	1.076
$E[w\|e_I]$	2.138	2.046	0.957	2.095	0.98	2.392	1.118
$E[w\|e_S]$	3.175	2.705	0.852	2.761	0.87	3.101	0.977
Res. W.	1.406	1.165	0.829	1.165	0.829	1.447	1.029

Table C.13: Peru - Estimated Parameters

	Primary		Secondary		Tertiary	
	Men	Women	Men	Women	Men	Women
ρU	0.0800	0.0427	0.4793	0.1858	1.3229	0.5062
	(0.0468)	(0.0398)	(0.2612)	(0.0565)	(0.0374)	(0.0549)
λ_F	0.2838	0.0802	0.2595	0.1627	0.4895	0.4508
	(0.0595)	(0.0171)	(0.0360)	(0.0286)	(0.0452)	(0.0404)
λ_S	0.4567	2.0834	0.3805	1.0895	0.6617	0.6736
	(0.0759)	(1.1200)	(0.0504)	(0.4362)	(0.2175)	(0.0486)
δ_F	0.0197	0.0325	0.0225	0.0214	0.0314	0.0390
	(0.0028)	(0.0073)	(0.0038)	(0.0035)	(0.0029)	(0.0035)
δ_S	0.0176	0.0963	0.0225	0.0376	0.0285	0.0666
	(0.0018)	(0.0382)	(0.0031)	(0.0206)	(0.0052)	(0.0060)
μ_F	1.6319	1.3617	1.6895	1.5393	2.0606	2.1616
	(0.0196)	(0.1866)	(0.0612)	(0.0275)	(0.0133)	(0.0163)
σ_F	0.0055	0.0286	0.0031	0.0035	0.0217	0.0040
	(0.0021)	(0.0108)	(0.0008)	(0.0010)	(0.0088)	(0.0012)
μ_I	1.2022	0.8186	1.1664	0.9976	-0.5798	-1.5607
	(0.0176)	(0.0443)	(0.0850)	(0.0432)	(0.0864)	(0.1454)
σ_I	0.0024	0.0009	0.0072	0.0039	1.0989	1.9203
	(0.0009)	(0.0264)	(0.0024)	(0.0011)	(0.0729)	(0.1155)
μ_S	0.4670	-0.2500	0.6618	-0.0873	-0.3841	-0.6274
	(0.0200)	(0.4952)	(0.1107)	(0.2537)	(0.4778)	(0.1764)
σ_S	0.6023	1.5907	0.4817	1.3992	1.1980	1.4102
	(0.0297)	(0.3640)	(0.0593)	(0.1706)	(0.1254)	(0.0736)
σ_{ME}	0.5999	0.6495	0.5999	0.6495	0.5999	0.6495
	-	-	-	-	(0.0075)	(0.0117)
γ	29.7031	25.5737	6.1053	5.9528	2.1426	3.0565
γ_{k5}	-	21.3520	-	4.9705	-	2.4312
γ_{k13}	-	29.7499	-	6.8259	-	3.3043
γ_{other}	-	28.3009	-	6.7401	-	3.6857
b	-18.0207	-36.1811	-17.338	-29.5757	-19.3774	-24.1667
c	0.2052	0.2052	0.2390	0.2390	0.2675	0.2675
Likelihood	-7714	-7810	-12471	-7028	-18485	-16129
N	3438	6132	5039	4319	6519	6898

Note: Bootstrap standard errors (based on 25 replications) in parentheses. Nonestimated parameters: β = 0.5, τ = 0.24, and ρ = 0.067.

Table C.14: Peru - Labor Market Dynamics and States

	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
h_u									
Data	0.964	1.355	1.406	0.878	1.398	1.591	0.765	0.895	1.169
Model	1.024	2.173	2.122	0.899	1.276	1.420	0.765	0.910	1.189
$h_{u \to e_F}$									
Model	0.284	0.080	0.283	0.259	0.163	0.627	0.490	0.451	0.921
$h_{u \to e_I}$									
Model	0.284	0.080	0.283	0.259	0.163	0.627	0.084	0.112	1.338
$h_{u \to e_S}$									
Model	0.457	2.013	4.407	0.380	0.951	2.504	0.192	0.347	1.810
u									
Data	0.019	0.025	1.302	0.025	0.033	1.282	0.038	0.048	1.240
Model	0.018	0.037	2.080	0.024	0.024	0.985	0.038	0.048	1.259
e_F									
Data	0.202	0.047	0.233	0.348	0.168	0.482	0.601	0.564	0.939
Model	0.259	0.092	0.355	0.282	0.183	0.650	0.600	0.560	0.933
e_I									
Data	0.315	0.143	0.454	0.215	0.222	1.034	0.102	0.134	1.316
Model	0.259	0.092	0.355	0.282	0.183	0.650	0.103	0.139	1.356
e_S									
Data	0.464	0.785	1.692	0.412	0.578	1.402	0.259	0.254	0.982
Model	0.465	0.779	1.676	0.412	0.610	1.479	0.259	0.252	0.975
np									
Data	0.093	0.336	3.619	0.054	0.331	6.175	0.059	0.213	3.622
Model	0.093	0.336	3.619	0.054	0.331	6.175	0.059	0.213	3.622

Table C.15: Peru - Policy Experiments

	Benchmark			P. Exp. No. 1		P. Exp. No. 2	
	M	W	W/M	W	W/M	W	W/M
Primary							
u	0.018	0.037	2.08	0.037	2.08	0.045	2.529
e_F	0.259	0.092	0.355	0.092	0.355	0.112	0.432
e_I	0.259	0.092	0.355	0.092	0.355	0.112	0.432
e_S	0.465	0.779	1.676	0.779	1.676	0.731	1.573
np	0.093	0.336	3.619	0.237	2.553	0	0.002
h_u	1.024	2.173	2.122	2.173	2.122	1.714	1.673
GDP_W	3.126	2.859	0.915	2.933	0.938	3.905	1.249
GDP_C	2.785	1.828	0.657	2.155	0.774	3.727	1.338
$E[w\|e_F]$	2.11	1.57	0.744	1.554	0.736	1.901	0.901
$E[w\|e_I]$	1.611	1.059	0.657	1.062	0.659	1.324	0.822
$E[w\|e_S]$	1.908	2.857	1.497	2.995	1.569	4.053	2.124
Res. W.	0.08	0.043	0.533	0.043	0.533	0.339	4.237
Secondary							
u	0.024	0.024	0.985	0.024	0.985	0.026	1.068
e_F	0.282	0.183	0.65	0.183	0.65	0.199	0.705
e_I	0.282	0.183	0.65	0.183	0.65	0.199	0.705
e_S	0.412	0.61	1.479	0.61	1.479	0.577	1.399
np	0.054	0.331	6.175	0.231	4.31	0.082	1.531
h_u	0.899	1.276	1.42	1.276	1.42	1.156	1.286
GDP_W	3.409	3.085	0.905	3.154	0.925	3.718	1.091
GDP_C	3.148	2.015	0.64	2.367	0.752	3.324	1.056
$E[w\|e_F]$	2.437	1.996	0.819	1.955	0.802	2.256	0.926
$E[w\|e_I]$	1.736	1.346	0.775	1.32	0.76	1.608	0.926
$E[w\|e_S]$	2.166	2.705	1.249	2.846	1.314	3.468	1.601
Res. W.	0.479	0.186	0.388	0.186	0.388	0.42	0.876
Tertiary							
u	0.038	0.048	1.259	0.048	1.259	0.049	1.277
e_F	0.6	0.56	0.933	0.56	0.933	0.568	0.946
e_I	0.103	0.139	1.356	0.139	1.356	0.139	1.354
e_S	0.259	0.252	0.975	0.252	0.975	0.244	0.943
np	0.059	0.213	3.622	0.139	2.37	0.135	2.292
h_u	0.765	0.91	1.189	0.91	1.189	0.892	1.166
GDP_W	6.21	6.464	1.041	6.493	1.046	7.227	1.164
GDP_C	5.62	4.842	0.862	5.318	0.946	5.947	1.058
$E[w\|e_F]$	3.827	3.76	0.983	3.743	0.978	4.194	1.096
$E[w\|e_I]$	2.201	2.314	1.051	2.486	1.13	2.798	1.271
$E[w\|e_S]$	3.529	2.585	0.732	2.582	0.732	2.953	0.837
Res. W.	1.323	0.506	0.383	0.506	0.383	0.656	0.496

Table C.16: Policy Effects on GDP per Capita

	Policy Exp. No. 1	Policy Exp. No.2
	Argentina	
Primary	6.7%	43.1%
Secondary	5.3%	11.2%
Tertiary	3.9%	15.2%
Total	5.0%	22.0%
	Chile	
Primary	5.9%	35.3%
Secondary	5.8%	9.0%
Tertiary	3.7%	9.4%
Total	4.6%	13.0%
	Colombia	
Primary	5.1%	32.3%
Secondary	4.4%	8.7%
Tertiary	3.4%	10.0%
Total	3.9%	13.4%
	Mexico	
Primary	6.1%	32.7%
Secondary	7.3%	8.9%
Tertiary	5.8%	12.8%
Total	6.4%	14.0%
	Peru	
Primary	7.4%	52.8%
Secondary	5.3%	22.0%
Tertiary	4.1%	10.3%
Total	5.0%	20.5%

Note: Percentage of GDP per capita with respect to the benchmark case.

Table C.17: Policy Effects on Participation Rates

	Benchmark M	Benchmark W	Policy Exp. No. 1 W	Policy Exp. No. 2 W
Argentina				
Primary	0.902	0.483	0.578	0.981
Secondary	0.950	0.614	0.703	0.706
Tertiary	0.922	0.793	0.850	0.893
Total	0.762		0.804	0.900
Ratio w.r.t. Benchmark			1.056	1.182
Chile				
Primary	0.849	0.361	0.429	0.697
Secondary	0.942	0.589	0.678	0.660
Tertiary	0.902	0.779	0.841	0.850
Total	0.722		0.763	0.807
Ratio w.r.t. Benchmark			1.056	1.118
Colombia				
Primary	0.924	0.550	0.631	0.976
Secondary	0.954	0.685	0.762	0.751
Tertiary	0.936	0.836	0.889	0.897
Total	0.802		0.841	0.906
Ratio w.r.t. Benchmark			1.049	1.130
Mexico				
Primary	0.859	0.309	0.377	0.613
Secondary	0.930	0.434	0.525	0.493
Tertiary	0.900	0.628	0.701	0.707
Total	0.650		0.696	0.720
Ratio w.r.t. Benchmark			1.071	1.107
Peru				
Primary	0.907	0.664	0.763	1.000
Secondary	0.946	0.669	0.769	0.918
Tertiary	0.941	0.787	0.861	0.865
Total	0.817		0.865	0.930
Ratio w.r.t. Benchmark			1.059	1.139

Table C.18: Policy Effects on Gender Gaps in Participation Rates

	Benchmark	P. Exp. No. 1	P. Exp. No. 2
		Argentina	
Primary	-0.42	-0.32	0.08
Secondary	-0.34	-0.25	-0.24
Tertiary	-0.13	-0.07	-0.03
Total	-0.3	-0.22	-0.04
		Chile	
Primary	-0.49	-0.42	-0.15
Secondary	-0.35	-0.26	-0.28
Tertiary	-0.12	-0.06	-0.05
Total	-0.33	-0.25	-0.17
		Colombia	
Primary	-0.37	-0.29	0.05
Secondary	-0.27	-0.19	-0.2
Tertiary	-0.1	-0.05	-0.04
Total	-0.24	-0.17	-0.06
		Mexico	
Primary	-0.55	-0.48	-0.25
Secondary	-0.5	-0.41	-0.44
Tertiary	-0.27	-0.2	-0.19
Total	-0.45	-0.37	-0.33
		Peru	
Primary	-0.24	-0.14	0.09
Secondary	-0.28	-0.18	-0.03
Tertiary	-0.15	-0.08	-0.08
Total	-0.22	-0.13	-0.01

Note: Percentage point gap in participation rates between men and women