Female Labor Force Participation, Labor Market Dynamic and Growth in LAC.*

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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 Caribbeans (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 of an increase in female labor force participation on labor market outcomes and GDP is therefore crucial but it is challenging. Two issues are of particular importance: sample selection and equilibrium effects. We develop a labor market model able to address these issues. We estimate the model on microdata for five LAC countries. We find that both a child care policy and a policy increasing women's productivity generate a positive impact on female participation and significant increases in GDP per capita. We claim our results suggest that relative modest policies able to increase the participation of women in the labor market can provide significant impacts on growth. 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.

Keywords: Female labor force participation; Labor market frictions; Search and matching; Nash bargaining; Informality.

JEL Codes: J24, J3, J64, O17

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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 it holds true in Latin America and the Caribbeans (LAC). For example, Busso and Fonseca [2015] show that average female labor force participation in LAC in 2010 was about 65% compared to about 76% in the US. There are important differences between LAC countries, with values ranging from the mid 50% of Honduras and Mexico to the high 70% of Peru and Uruguay.

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 GDP. The potential positive impact of bringing more women to the labor market has been increasing over time since women are acquiring more and more human capital with each passing generation. For example, schooling completed among women is now higher than men in all high income economies and in many LAC economies. Argentina, Brazil, Colombia, Uruguay: all report a positive gender gap in years of schooling completed, i.e. women have on average more years of schooling completed than men. The aggregate average for LAC in 2012 is a small positive gender gap in favor of women contrasting with a half year of negative gap in 1992.[2]

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

1.2 Challenges

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

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

[2] See Marchionni [2015] for more details. The aggregate result is strongly driven by younger generations: the age group 25-34 shows a strong positive gap in favor of women, the 35-44 group a small positive gap while the 45-54 a strong negative gap. All data refer to 2012.

1. Sample selection;

2. Equilibrium Effects.

Sample selection refers to the difference in the type of individuals that are participating in the labor market with respect to those that are not. When we observe men and women currently offering labor in the market, earnings some specific wages and contributing some specific productivity to the country's economy, we have to consider that a large proportion of women do not work. Therefore the women that are currently working may be different from those that would enter the labor force as a result of policies able 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 Effects 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 a given 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 and 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 a first, *short-run equilibrium effect*. Eventually, labor demand will also adjust since firms may decide to change their production mix and post more or less jobs at different skill levels. This demand-side behavior has also the potential to change wages and earnings and it is a second, *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 wage and earnings *before* the increase is taking place. This is due to the fact that the observed data are extracted from an equilibrium which is different than the one realized *after* the increase in participation is taking place.

1.3 Approach

A possible approach able to take into account sample selection and equilibrium effects consists in specifying an economic model which includes the channels generating the effects. Micro-level 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 where the quantitive impact of an increase in female labor force participation can be estimated taking into account selection and equilibrium effects.

We propose such 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 into account sample selection because the optimal decisions implemented by the agents are sensitive to the policy parameters. Moreover, workers decision rules can be explicitly characterized taking into account 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 we will limit our analysis to take into account short-run equilibrium effects and some selections effects.

Search models of the labor market are widespread and influential[3] since they introduce labor market dynamic, equilibrium unemployment and non-competitive features in a tractable and empirically relevant model of the market. Their use to answer policy questions using micro-data has a long tradition: for example, Eckstein and Wolpin [1995] study returns to schooling; Ahn et al. [2011] and Flinn [2006] evaluate the employment and welfare impact of minimum wage legislation; Dey and Flinn [2005] the impact of employer-provided health insurance; Flabbi [2010] the effect of affirmative action legislation; and Cahuc et al. [2006] the impact of workers' bargaining power. Recent contributions have used this approach to answer policy questions in LAC: Tejada [2017] focuses on the distortions of introducing multiple labor contracts while Bobba et al. [2017] assess the effect of non-contributory benefits, informality and long-term impacts on education.

In order to adapt this approach to labor markets in LAC is important to consider 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 in order to capture the systematic differences in their observed labor market dynamic. Individuals are allowed to move optimally between labor market states and may choose to do so as a result of shocks and new opportunities.

An additional step is needed to adapt the framework to the study of female labor force participation: a labor supply decision. We introduce an endogenous participation decision as a function of individual heterogeneity over out-of-labor-market market utility. The out-of-labor-market utility is allowed to vary by the observable characteristics which is considered

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

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 take into account 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 which is affected by policy variables and by optimal individual behavior. This approach dates back to at least Eckstein and Wolpin [1995]. In the gender literature, it has been used by Flabbi [2010] to evaluate affirmative action policies in favor of women. In the gender literature in LAC, it has been used by Tejada and Perticara [2016] to estimate the presence of discrimination against women.

There are two main advantages in the proposed approach. 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 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 micro data. We see this as an advantage with respect to quantitative exercises based on calibrated macro models such as the interesting exercise performed on a variety of both OECD and non-OECD countries by Cuberes and Teignier [2016]. 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 possibility 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 project is organized as follows. The next section provides a description of the data used in Estimation. Section 3 sketches out the formal economic model used in estimation. More details and all the technical material are reported Appendix A. Section 4 briefly presents the estimation method and the identification strategy with the complete treatment relegated to Appendix B. Section 5 presents the main estimation results and the policy experiments. Complete results are available in Appendix C. Section 6 concludes.

2 Data

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

- Labor market status;
- Hourly wages or earnings;
- On-going durations in the labor market state or transitions matrixes between labor market states;
- Demographic characteristics;
- 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 survey leading to survey dates ranging from the third quarter of 2014 to the last quarter of 2016. In the case of Argentina, we use the *National Survey of Urban Households* (EAHU) conducted in the third quarter of 2014. It is a rapresentative household survey collected by the *National Institute of Statistics and Census* (INDEC) with a cross-sectional structure and reporting information on education, labor force variables and income. In the case of Chile, we use the *National Socio-Economic Characterization Survey* (CASEN) of 2015. It is conducted between November 2015 and January 2016. It is a cross-sectional household survey representative at a national level and reports information on education, labor force, income, and health status. In the case of Colombia, we use the *Great Integrated Household Survey* (GEIH) of the last quarter of 2016. It is a monthly cross-sectional household survey describing labor force status, the quality of life, income and expenditures. 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 markets status and characteristics. Finally, for Peru the *National Household Survey* (ENAHO) of 2016. It is a quarterly cross-sectional household survey representative at a national level and reports information on education, labor force, income, and household expenditures.

To build the estimation samples, we extract all the individuals aged between 25 and 55 years old and working in non-agricultural activities. Both restrictions are motivated by ensuring a more homogenous sample of workers. Labor market careers typically exhibit life-cycle patterns. Our approach is not well equipped to capture them and therefore our age restrictions eliminates some of the major life-cycle dynamics (such as retirement concerns or first-entrants). A shorter age range would have guaranteed more homogeneity but the cost in terms of sample size would have been too large, in particular on some countries. The compromise we reached by considering only 25-55 years old generates an age range similar to the one used in comparable literature.[4] The focus on non-agricultural activities is dictated by the theoretical model. Our proposed search model with bargaining is a good – and commonly used – description of labor markets characterized by a clear division of labor and by work for pay. These characteristics are less predominant in the agricultural sectors of most of the countries under consideration and therefore our theoretical model would have not been a good description of them.

We then divide the sample based on the highest level of education completed: Primary school or less, Secondary school, and Tertiary level degree and above. We define four labor market states from the observed data: Unemployed, Formally employed as employee, Informally employed as employee, Self-employed. We also consider the state of no labor market participation. Following Kanbur [2009] and Levy [2008], an employee is defined as informal when not contributing to the social security system. In most LAC countries, firms are obligated to enroll salaried workers in the social security system and pay contributions which are approximately proportional to wages. Observing this registration in labor market data is considered in the literature a reliable measure of informal employment. Self-employed workers have typically different requirements but they rarely enroll and pay contribution in the system. The overall informal sector is therefore frequently considered the sum of the self-employed and the informal employees (Bobba et al. [2017] and Meghir et al. [2015]). When considering women, we also report the presence of young children in the household. We consider two cutoffs based schooling age: for pre-schoolers we use the cutoff at 5 years of age and for primary and lower-secondary we use the cutoff at 13 age of age. In this way, we are able to identify women with children who are still not old enough to be enrolled in compulsory schooling and women with children who are in the age range typically covered

[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.

by compulsory schooling in the Region.

Tables 1, 2, 3, 4 and 5 report descriptive statistics on the samples we use in estimation. Figures 1 and 2 focus on one of the feature we are most interested in: participation rates. Figure 1 shows that in all countries there is a strong gender asymmetry in participation rates. At least 90% of men participate in the labor market in all countries while female participation ranges from about 45% in Mexico to about 71% in Peru. Figure 2 shows that the overall female participation rates mask 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 completed and women with only primary education completed is more than 30 percentage points.

Tables 1, 2, 3, 4 and 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 US Dollars[5] ($\bar{w}$); and the standard deviation of wages expressed in 2016 US Dollars (σ_w). The unemployment durations are generally short, ranging from about to 2 to about 4 months on average. The exception is Peru where durations are extremely short, less than 2 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 common in other middle-income countries and in 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 in Mexico with Tertiary education where the gap is almost zero.

3 Model

We propose a search model of the labor market able to capture the specific characteristics of LAC labor markets and to account for the endogenous labor supply decisions of women. We have chosen this approach to solve some of the challenges generated by estimating the

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

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 informal work (see for example Meghir et al. [2015]). However, we follow contributions more attuned to the institutional details of the region – such as Anton et al. [2012] and Bobba et al. [2017] – in differentiating the informal sectors in these two distinct labor market states. To adapt the framework to the study of female labor force participation, we add a labor supply decision. Women endogenous participation decision is a function of their specific utility in out-of-labor-market activities. The out-of-labor-market utility is allowed to change if young children are present in the household.

3.1 Environment

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

When non-participating, workers receive a flow utility z which is potentially different for each agent in the economy. 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 effort and other costs related to search and unemployment are higher than the benefit of not working. Job opportunities arrive at a gender- and employment-type specific Poisson rate λ_{ij}. If a job is accepted, subsequent job termination is possible and exogenous. Termination shocks arrive at a gender and employment type specific Poisson rate δ_{ij}.

A job opportunity is characterized by a match-specific productivity x, which we model as a draw x from the distribution $G_{ij}(x)$. Once an employee is hired, receives a wage $w_{ij}(x)$ which is a gender- and labor relation-specific 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.[7] 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. It is equivalent to model this cost has a probabilistic one-shot cost or as a deterministic flow cost. For simplicity, we use the second parameterization. The penalty is therefore modeled as a constant flow cost c. The future is discounted at a rate ρ common to all the agents in the economy.

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:

$$\begin{aligned}\rho U_i &= b_i + \lambda_{iF} \int \max\left[E_{iF}(x), U_i\right] dG_{iF}(x) + \lambda_{iI} \int \max\left[E_{iI}(x), U_i\right] dG_{iI}(x) \\ &\quad + \lambda_{iS} \int \max\left[E_{iS}(x), U_i\right] dG_{iS}(x) - (\lambda_{iF} + \lambda_{iI} + \lambda_{iS}) U_i \end{aligned} \tag{1}$$

The interpretation is intuitive. When a worker is unemployed, receives utility b_i for sure every period. Moreover, she has the possibility of meeting an employer offering a formal or an informal job (respectively, with probability λ_{iF} and λ_{iI}). Finally, she can receives a self-employment opportunity with probability λ_{iS}. Every time she receive 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 are as follows. If she accepts the offer, she receives labor income; if she she rejects, she 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.

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

3.3 Wage Determination

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

The actual wage paid to the workers is decided by bargaining, i.e. worker and firm make offers and counter-offers taking into account their outside options. Their outside options are the state they will be in if they reject the offer. For the worker, it is the state of unemployment; for the firm, it is the state of having a vacancy open at the firm. Additionally, workers and firms may have a stronger or weaker bargaining power, which include everything else that may put the agents in a stronger bargaining position. We denote this parameter with β.

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 different 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 utility from out-of-labor-market activities (state NP). Since women receive different utility from these activities (z), women receiving relative high utility will stay out, women receiving relative low utility will enter the market. The threshold for staying out or coming in is determined by the indifference point between the two states, i.e. by the specific z_i^* such that:

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

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 searching for a better offer. As before, the threshold is identified by the indifference point between the two alternatives, i.e. by the specific x_{ij}^* such that:

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

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

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

notice that these threshold have some economic interpretation. In particular, employee relationships require higher productivity to be acceptable because the worker has to share with the employer. Moreover, the employer has to pay either contribution or illegality costs and therefore the thresholds are increasing in those parameters. In conclusion, every time an unemployed women will receive a wage offer 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. Analogous behavior at different parameters is realized by men.

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, the solved value function and the steady state conditions can be used to determine the equilibrium levels of non-participation (np_i), unemployment (u_i), and employment ($e_{i,j}$) for each gender. Again, details are in Appendix A.

4 Identification and Estimation

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 on-going unemployment duration (u). Each of the 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 allow for the derivation of the likelihood contribution of each observation in our sample (see Appendix B). From the likelihood contributions, it is possible to formally prove 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 and 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. While theoretical identification of β is assured by the model's implications and by the distributional assumptions, its empirical identification is challenging without demand side information[8] and that is why we simply calibrate the parameter to the value of symmetric Nash bargaining. This is definitely a restriction in our context since it force us to the set the same Nash bargaining parameter to men and women. Previous literature has shown that differences in β by gender are likely to be present and they are often interpreted as capturing discrimination or gender-specific attitudes toward negotiation.[9] Even if we have to impose the restriction, it is worth remembering that the presence of endogenous and gender-specific outside options (U_i) still allows the wages to capture differences in bargaining power between men and women. Since the outside option enters directly in the wage equations, a lower outside option for a given gender in a given schooling group translates into lower wages at same productivity compared with the other gender.[10]

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 negative exponential with parameter $\gamma_{i\kappa}$. The subscript $_{i\kappa}$ denotes that the parameter is not only a

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

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

[10] See equations 2 and 3.

function of gender i but also of the presence of young children in the household. We consider three age groups: household with at least one child younger than 5 ($\kappa = k5$); household with at least one child between the age of 5 and 13 but no children younger than 5 ($\kappa = k13$); and households where there are no children younger than 13 ($\kappa = other$). After preliminary analysis, we concluded that the estimates on men were not sensitive to the presence of children and therefore we introduce these differences only on the women's specifications. 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 being normal with mean zero and variance σ^2_{ME}.

5 Estimation Results and Policy Experiments

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

Tables 6 through 10 report the implications of the parameters estimates on productivity and wages. The top panel of each table reports expected value ($E[x]$) and standard deviation ($SD[x]$) of the match-specific productivity in formal employment, informal employment and self-employment. They describe the primitive productivity distributions that we denoted with $G_{ij}(x)$ in the formal modal and they represent the potential output of a given match between a worker and a firm. Some of these matches are realized (accepted) and some are not, depending on the optimal decision rules of the agents (see Section 3.4). The bottom panel of each table reports expected value and standard deviation of the accepted wages in formal employment and informal employment and of the realized labor income in self-employment.

Notice that the relation between the top panel and the bottom panel involves two steps. The first step is the mapping between a specific value of productivity x and the wage paid to the worker w. This relation is governed by the equilibrium equations 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: (i) agents may spend time in different labor market states, including unemployment; (ii) agents may be less or more productive if they work formally or informally; and, (iii) some agents may not participate in the labor market at all. The 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 both 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 favor men, 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 employee 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.[11] It is important to notice that a gender gap in productivity in favor of women rarely translates in a similar gap in accepted wages. Again looking at tertiary educated women in Peru, the last column of the bottom panel shows 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.

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

The bottom panel is useful to assess gender gaps in accepted wages but also to judge how well the estimated model fit 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.

5.2 Policy Experiments

We propose two policy experiments that may clarify both the reason behind and the loss implied by the lower labor market participation of women with respect to men. Women may decide to participate less then men either because the value of non-participation is higher or because the benefit of participating in the market is lower. The first experiment relates to the first component – the value of non-participation – and the second experiment to the second component – gender asymmetries in labor market opportunities.

Both opinion surveys and economic literature indicate that women value more than men time outside the labor market.[12] Our own estimates show this to be the case since the average value of non-participation $E(z)$ is estimated to be higher for women than men in all education groups. Many factors may impact this difference, such as preferences, household production, abilities and attitudes. One major component seems to be child-care and child-rearing. Women still invest an higher amount of hours in child-care than men and their labor market participation is significantly affected by fertility outcomes [Burda et al., 2013]. Many policy tools may have an impact on this value. For example, good and affordable childcare provisions may decrease the benefit of mother's time in child-rearing and induce them to work more. To map this policy in our model we change the parameters governing the flow utility of non-participation z. Recall that this value is heterogenous 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 non-participation to be different between women with children younger than 5, children between the age of 5 and 13, and without children younger than 13. Since child-care provision policies are more likely to affect mother with young children, *Policy Experiments 1* reduces the average value of non-participation for those mother in half. Formally, it is equivalent to doubling the parameter γ_{k5}.

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

Gender asymmetries in labor market opportunities are the results of many components, including the gender wage gap, differences in promotions and labor market careers, asymmetries in search intensity and occupational choices. Some of these differences may be due to differences in preferences and attitudes but other may relate to issues affected by policies such as human capital accumulation, gender discrimination, occupational choices. For example, a policy that gives incentive to women to enroll in STEM or an affirmative action policy aiming at reducing discrimination can both be seen as policies boosting women productivities.[13] In this spirit, *Policy Experiments 2* increases the average productivity of women in the three sectors by 10%. Since productivity is represented in our model by the distributions $G_{i,j}(x)$, formally, the experiments changes the parameters μ_{Wj} and σ_{Wj} for $j = F, I, S$ so that the new average productivity $E_{Wj}(x)$ is 10% higher. We chose 10% to ease the calculation of the elasticities but it is worth noticing that in many cases a 10% increase is enough to close the gender gap in productivity. This is true in most countries among workers with secondary and tertiary education completed.[14] Among workers with only primary education completed, instead, the gaps are typically larger, ranging from 20% to 30% and therefore a 10% increase is not enough to generate the same average productivity between men and women.

Figures 3 through 7 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. The increase in participation translates in an increase in GDP thanks to the larger proportion of women in the labor market. The increases in GDP per capita are reported in Figure 4 and they are substantial. For example the GDP per capita in Mexico and Peru 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%. On top of differences by countries, there differences by education groups. 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.

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

[14] A notable exception is Chile, which is registering the largest gender gap in productivity in the tertiary education group: we estimate the average productivity of women about 20% lower than the average productivity of men. See the last column of Table 7.

Figure 5 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 this group, the participation rate increases by more than 30 percentage points leading to full participation in the case of Colombia and Peru. As expected, the impact on GDP per capita is very large among these groups, as reported in Figure 6. However, the impact on overall GDP per capita, while still large, is not as massive since 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 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 7. The overall increase is decomposed in the portion directly due to the 10% productivity increase (Pure Productivity Effects) and the portion due to the increase in participation resulting from the productivity increase (Labor Force Effect). 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, since the agents are faced with a new environment (higher productivity) they will change their participation decision accordingly. The Figure 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 increase GDP by more than 10%.

6 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 in order to address these challenges consists in specifying an economic model which includes some of the most important channels generating these bias, including the endogenous labor market participation decision of women. Micro-level 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 child care policy while the second is equivalent to increasing female productivity by 10%. 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 relative modest policies able to increase the participation of women in the labor market can provide significant impacts on growth. 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.

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	-	-	-
$K < 5$						1750	0.44			
$5 < K < 13$						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	-	-	-
$K < 5$						772	0.42			
$5 < K < 13$						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	-	-	-
$K < 5$						506	0.38			
$5 < K < 13$						292	0.22			

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

Table 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	-	-	-
$K < 5$						3201	0.31			
$5 < K < 13$						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	-	-	-
$K < 5$						3067	0.41			
$5 < K < 13$						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	-	-	-
$K < 5$						1314	0.39			
$5 < K < 13$						769	0.23			

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

Table 3: Colombia - Descriptive Statistics

Labor Market	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w	N	Prop.	$\bar{t}_u$	$\bar{w}$	σ_w
States	Men					Women				
Education Group: Primary										
Unemployed	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	-	-	-
$K < 5$						1870	0.34			
$5 < K < 13$						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	-	-	-
$K < 5$						1272	0.38			
$5 < K < 13$						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	-	-	-
$K < 5$						893	0.41			
$5 < K < 13$						516	0.24			

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

Table 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	-	-	-
$K < 5$						3727	0.36			
$K < 13$						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	-	-	-
$K < 5$						7809	0.43			
$K < 13$						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	-	-	-
$K < 5$						2115	0.33			
$K < 13$						1545	0.24			

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

Table 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	-	-	-
$K < 5$						1014	0.49			
$5 < K < 13$						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	-	-	-
$K < 5$						716	0.50			
$5 < K < 13$						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	-	-	-
$K < 5$						717	0.49			
$5 < K < 13$						361	0.25			

Note: Wage distributions are trimmed at the top and bottom 1 percentile by gender, education group and type of job, and are reported in US Dollars of December 2016 (Exchange Rate = 3.395 Soles/US). A worker is categorized as informal if he/she reports not having access to health care. K means proportion of women with the presence of kids in the household with respect to non participating women.

Table 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

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

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

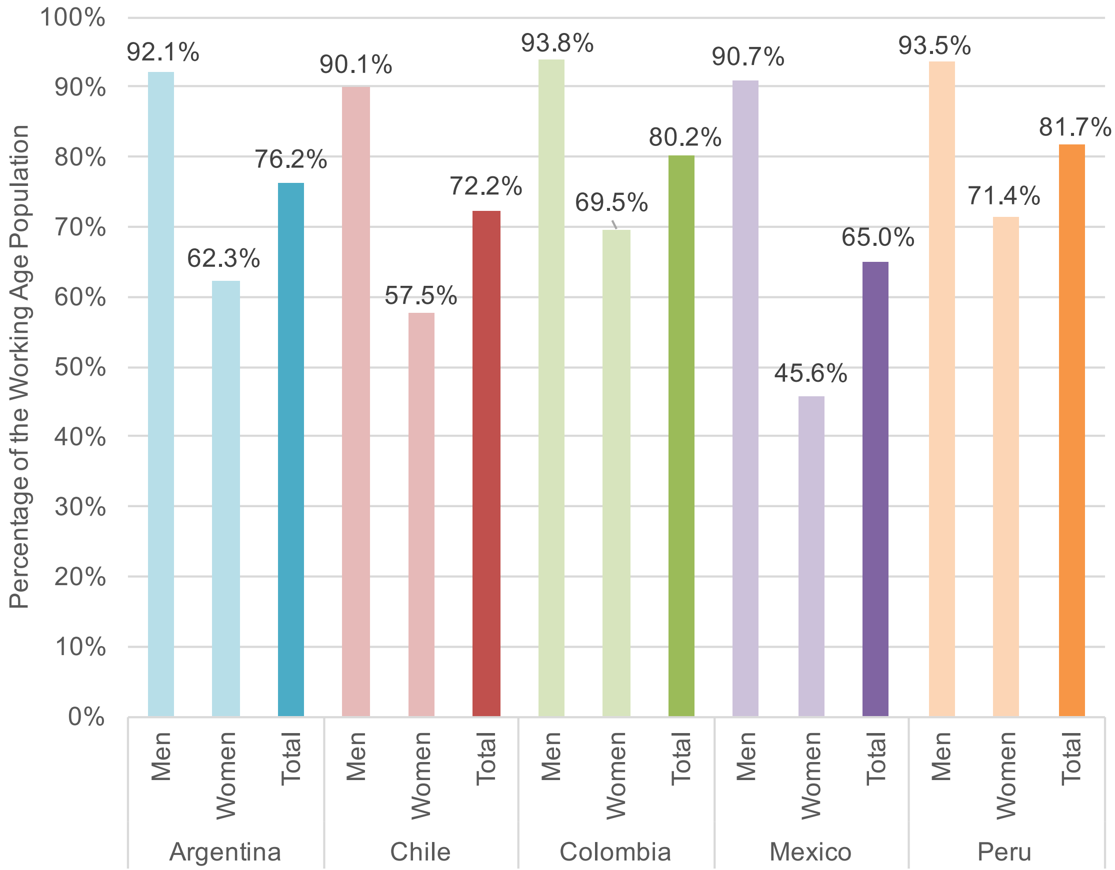
Table 9: Mexico - Productivity and Wages

	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

Table 10: Peru - Productivity and Wages

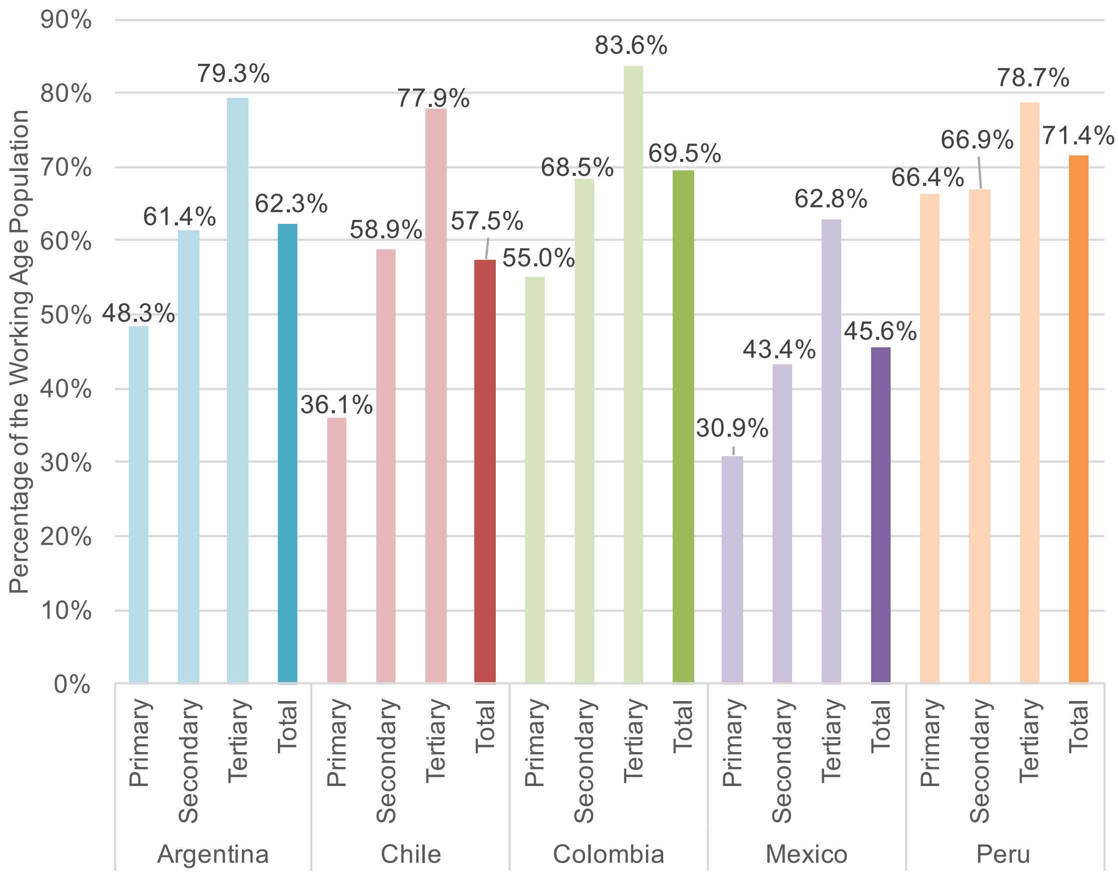
	Primary			Secondary			Tertiary		
	M	W	W/M	M	W	W/M	M	W	W/M
$E[x_F]$									
Model	5.114	3.904	0.764	5.417	4.661	0.860	7.852	8.685	1.106
$SD(x_F)$									
Model	0.028	0.112	3.978	0.017	0.016	0.988	0.170	0.035	0.203
$E[x_I]$									
Model	3.327	2.267	0.681	3.211	2.712	0.845	1.024	1.327	1.296
$SD[x_I]$									
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

Figure 1: Participation Rates by Gender



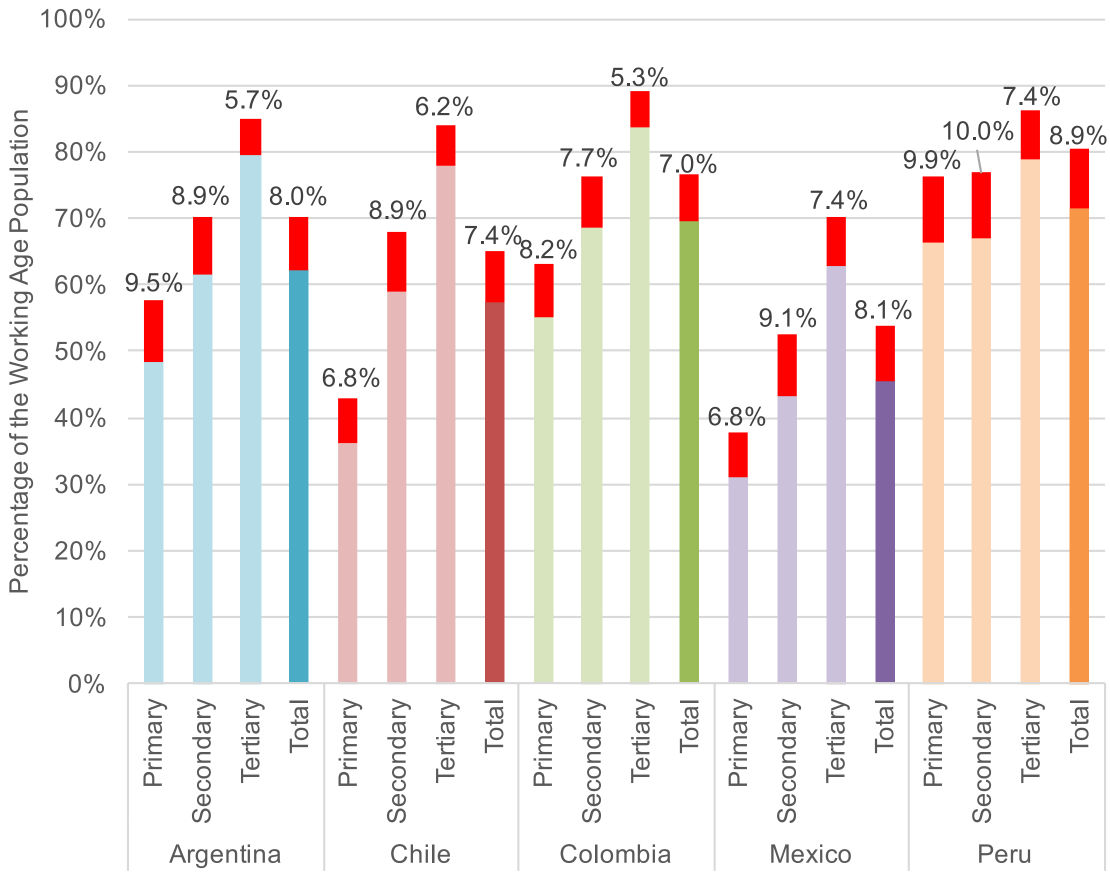
Note: Values are computed on the estimation samples for each country. See Section 2 for data sources.

Figure 2: Female Participation Rates by Education



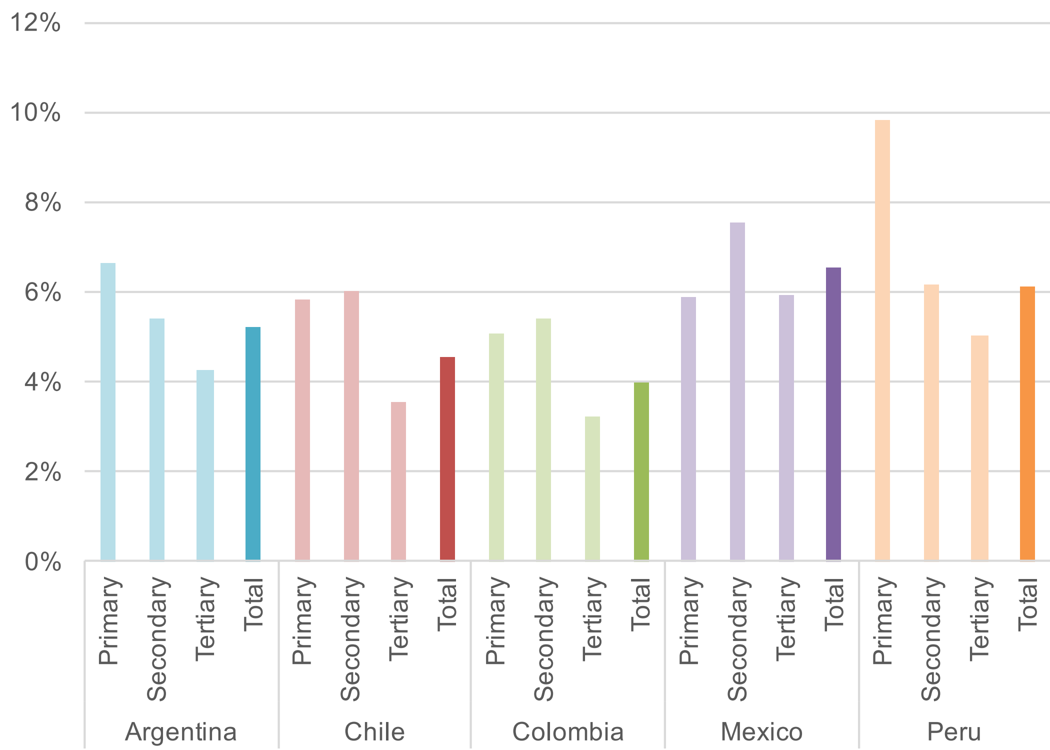
NOTE: Values are computed on the estimation samples for each country. See Section 2 for data sources.

Figure 3: Child-care Provision Policy: Impact on Female Participation Rates



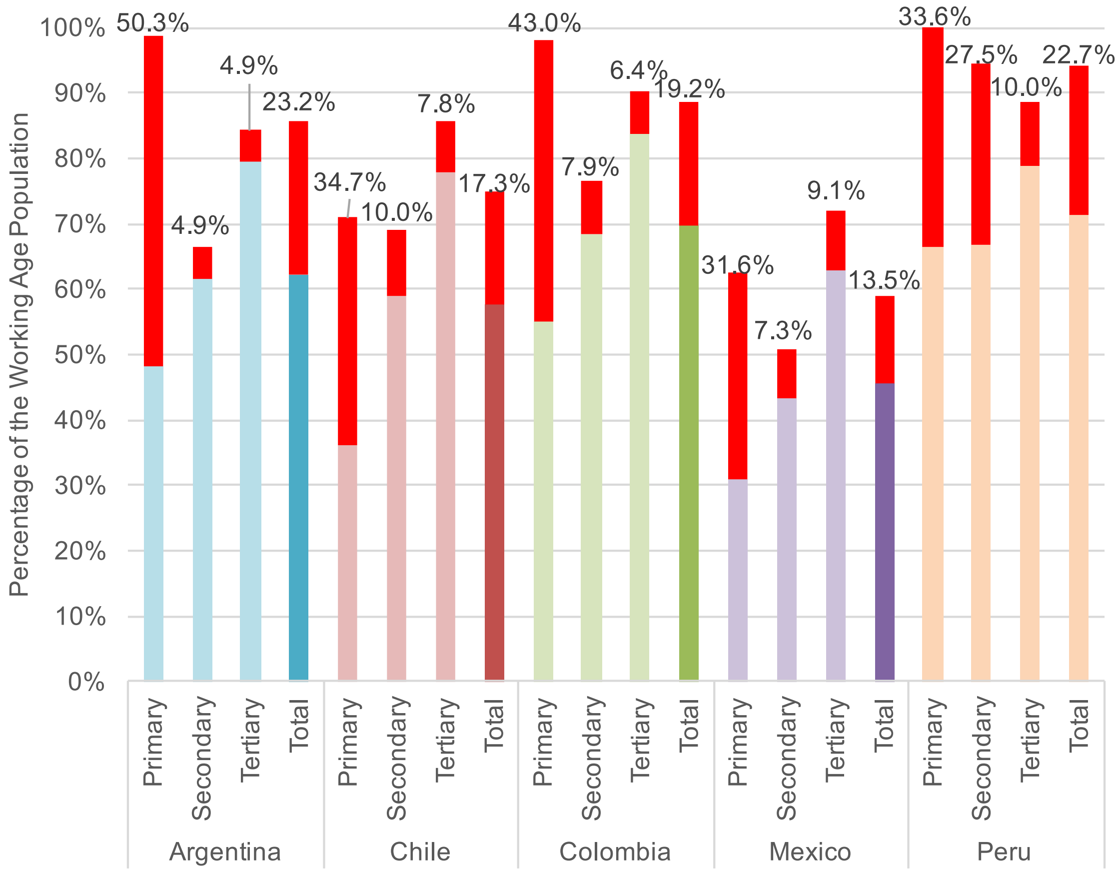
NOTE: The number on top of each column reports percentage points changes in participation rates as a result of *policy experiment 1*: reducing in half the average value of non-participation for mother with children younger than 5. See Section 5.2 for more details.

Figure 4: Child-care Provision Policy: Impact on GDP per Capita



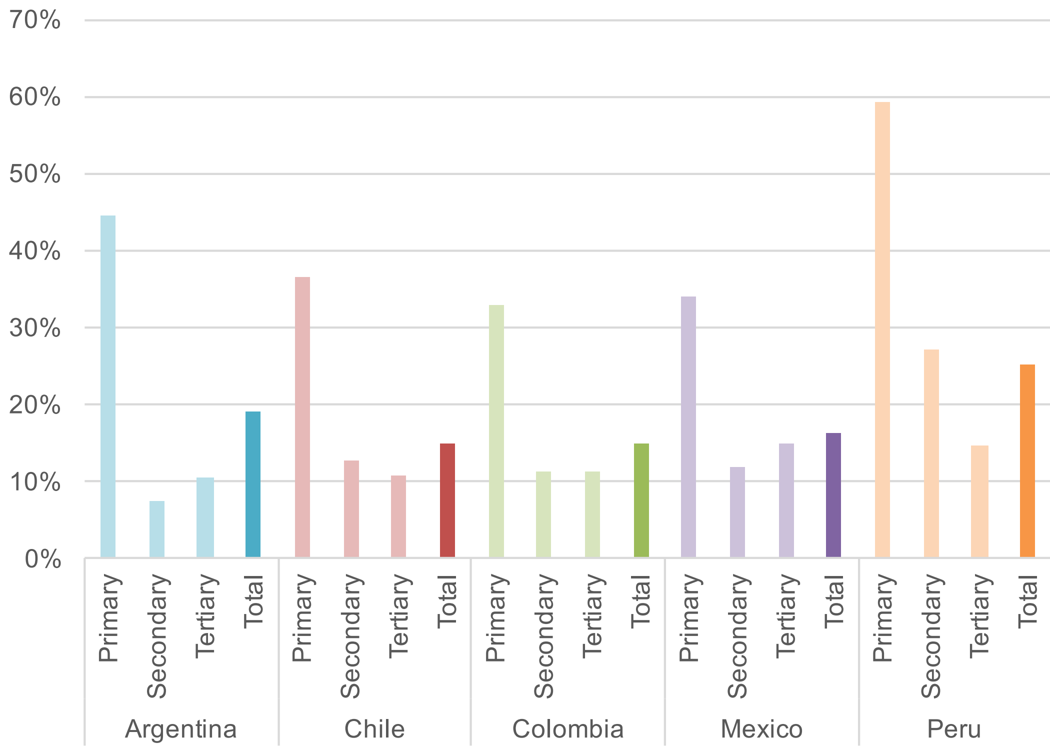
NOTE: Figure reports percentage points changes in GDP per capita as a result of *policy experiment 1*: reducing in half the average value of non-participation for mother with children younger than 5. See Section 5.2 for more details.

Figure 5: Increase Female Productivity Policy: Impact on Female Participation Rates



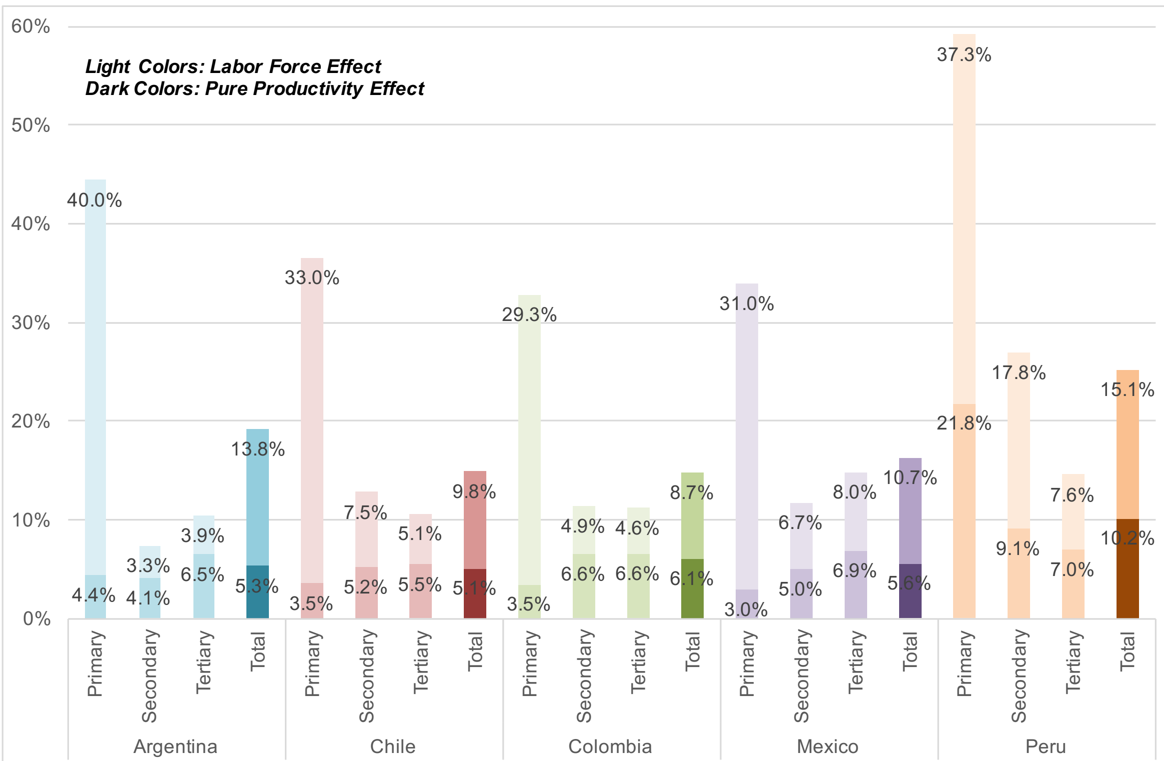
NOTE: The number on top of each column reports percentage points changes in participation rates as a result of *policy experiment 2*: increasing the average productivity of women by 10%. See Section 5.2 for more details.

Figure 6: Increase Female Productivity Policy: Impact on GDP per Capita



NOTE: Figure reports percentage points changes in GDP per capita as a result of *policy experiment 2*: increasing the average productivity of women by 10%. See Section 5.2 for more details.

Figure 7: Increase Female Productivity Policy: Impact on GDP per Capita by Channel



NOTE: Figure reports percentage points changes in GDP per capita as a result of *policy experiment 2*: increasing the average productivity of women by 10%. See Section 5.2 for more details. The overall increase is decomposed in the portion due to the 10% productivity increase (Pure Productivity Effects) and the portion due to the increase in participation resulting from the productivity increase (Labor Force Effect).

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