Assessing the Impact of Childcare Expansion in Mexico: Time Use, Employment, and Poverty

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1. Introduction

There is broad consensus in both research and policy circles that one of the key reasons for a lack of progress in reducing gender gaps in employment and wages is the persistent gender imbalance in unpaid work (Elson 2017; Ferrant, Pesando, and Nowacka 2014; Razavi 2007; Himmelweit 2002; Craig 2005). An analysis of global time use data shows that unpaid care work constitutes as many as 2 billion work hours per day, of which three quarters are performed by women (Addati et al. 2018).

The gender gaps in unpaid work (household production) and the gender gaps in paid work (market production) feed off one another. In most labor markets, the gender employment and wage gaps between mothers and fathers are substantially higher than those between women and men without dependent children (Misra, Budig, and Boeckmann 2011; Budig, Misra, and Boeckmann 2012, 2016). The more time women devote to unpaid household production, the less time they can commit to paid market work. Women from households whose members require care and that remain in employment---particularly women with low wages and hence limited ability to afford market substitutes for domestic work---suffer from a high workload imposed by their dual (domestic and workplace) shift. Some empirical studies have formalized this phenomenon as higher rates of time poverty amongst employed women (see Aloè 2020 for Italy; Zacharias, Antonopoulos, and Masterson 2012 for Argentina, Chile, and Mexico; Zacharias, Masterson, and Memis 2014 for Turkey; and Zacharias et al. 2019 for Ghana and Tanzania).

Against this background, the Recognition, Reduction, and Redistribution of unpaid care work (the so-called 3R strategy) has been accepted as a primary policy intervention towards closing gender gaps (UN Commission on the Status of Women 2014). Investing in social care services infrastructure is an important component of the 3R strategy. Universal access to quality care services enables the reduction of unpaid care work, borne disproportionately by women, through its redistribution from the domestic sphere to the public sphere. Numerous empirical studies from different regions and countries have found that access to services (in particular, childcare services) substantially increases female labor force

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participation and labor market attachment (see for example, Ettner 1995, Apps and Rees 2004, 2005, Sauer and Del Boca 2006 for Europe; Diaz and Rodriguez-Chamussy 2013 for Latin America and Caribbean; Halim, Johnson, and Perova 2018 for Asia).

A series of recent empirical studies show that access to care also creates new demand for female employment. Using a macro-simulation model, the studies compare the potential effects of increasing public expenditures on social care versus physical infrastructure, in terms of these short-run demand-side effects (Antonopoulos and Kim 2008 for South Africa; Ilkkaracan, Kim, and Kaya 2015 for Turkey; and Antonopoulos et al. 2010a for the USA). Given the labor intensity of the care services sectors and hence their high employment multipliers, increasing public spending on care is found to generate 2-to-3 times the number of new jobs per dollar than spending on other sectors such as construction. The studies on Turkey and the USA also included microsimulation components, which show that the increase in labor demand is pro-women, given the gender composition of employment in the care sectors. Thus, spending on care narrows the gender employment and wage gaps (as opposed to spending on construction, which further widens them). Finally, the higher employment intensity translates into generation of higher wage earnings for more households and hence stronger poverty reduction.

ONU Mujeres (2021) has produced aggregate estimated impacts of three social infrastructure interventions in the system of social provision in Mexico: universal free quality childcare; extended school days for school age children; and provision of universal elder care. In each case the estimates have utilized synthetic sectors created for the specific intervention, based on the Input-Output table for Mexico. These estimated impacts include the overall cost of each intervention, the aggregate impact on output and employment, as well as the impact on the fiscal balance for the government of Mexico. These types of estimates are similar to work done on the care sector in the United States, South Africa, Turkey, Ghana, and Tanzania (Antonopoulos and Kim 2011; Antonopoulos et al. 2010b; Zacharias et al. 2019; Ilkkaracan et al. 2021). Building on the prior literature and the studies carried out by ONU Mujeres, we aim to explore empirically the multiple gendered economic outcomes of care services expansion in terms of both employment creation and earnings generation as well as the changes in the unpaid and paid workload of women versus men and the associated risk of time poverty.

While investing in social care creates jobs and enhances access to employment and earnings for some women and men, it also increases the requirements on their time through higher hours of employment, increasing their risk of time poverty. Simultaneously, access to services alleviates the household production responsibilities of those with care-dependent household members. The net welfare impact for different groups of women and men taking both time- and income-effects into consideration is an empirical question. Thus, a comprehensive evaluation of the overall gendered wellbeing impact of investing in care requires a framework that keeps track of all these simultaneous outcomes. This report outlines a comprehensive analytical framework for the exploration of these multiple simultaneous outcomes using Mexican data on employment, income and time-use. We evaluate the trade-offs between time and income and attempt to identify the net impact on wellbeing on an empirical basis.

We follow studies on Ghana and Tanzania (Zacharias, et.al. 2019) and Turkey (Ilkkaracan et al. 2021), which address this empirical question using a combined measure of time- and income-poverty called the Levy Institute Measure of Time and Income Poverty (LIMTIP). Unlike conventional measures of poverty which focus only on income (or consumption expenditures), the LIMTIP also employs an accounting of the time required for household production of goods and services through unpaid work. This framework allows the estimation of policy impacts not just on household income and consumption expenditures but on individuals' time spent on unpaid work as well. An application of LIMTIP requires a combined dataset of time-use and income whereby it becomes possible to look at the interactions of labor market characteristics, earnings, paid versus unpaid work time and assess households as 'income poor', 'time-poor' or both.

Zacharias, et.al. (2019) and Ilkkaracan et al. (2021) construct combined (time-use and -income) datasets for Ghana, Tanzania, and Turkey to explore the gendered outcomes of childcare services expansion and reduction of unpaid household production time.[2] They also consider the changes in paid work time of workers into the new jobs generated through increased public spending on care services expansion. The findings reveal several interesting effects: the increased spending on care directly reduces employed women's time poverty; the employment generated reduces poverty via additional household income, though this is attenuated by higher time deficits for many; and the overall impact is to reduce the incidence of both time and income/consumption poverty for women in all three countries.

The paper builds on prior research on time and income poverty in Mexico (Zacharias, Antonopoulos, and Masterson 2012), aggregate estimates of employment changes produced by ONU Mujeres (2021), as well as the studies on Turkey, Ghana and Tanzania mentioned above. To this end we first construct a combined time-use and income-employment dataset for Mexico and use this as the basis for our policy simulation with a micro modelling methodology. We deploy a multi-staged microsimulation model to distribute the new jobs from the interventions (estimated by ONU Mujeres) to the non-employed but employable women and men observed in our data; we estimate the change in their earnings, paid and unpaid work hours, and evaluate the net effect of these changes on time- and income poverty by gender.

We find that time and income poverty in Mexico is high. The time poverty rate for employed women is 46.2 percent, much higher than for employed men (31.6 percent). Employed women in households with young children experience even greater rates of time poverty (53.8 percent). Income poverty rates are also high. When adjusted for time deficits, the income poverty rate for all employed individuals rises to 55.3 percent. This is 8.7 percentage points higher than the official measure, implying that a great number of individuals are in households that do not have the additional income needed to offset the time deficits they face to maintain the standard of living represented by the official poverty line.

We find that the expansion of early childhood education (ECE) services will substantially reduce time poverty rates. Employed women's incidence of time poverty drops by 8.1 percentage points (to 44.3 percent), while that of employed men drops by 3.5 percentage points (to 30.1 percent). We find that the estimated 3.9 million additional jobs created by expanding ECE services for Mexico creates a substantial increase in time-poverty among women. Accounting for the simultaneous increased access to ECE services, the time-poverty rates of women with small children who received a new job in the simulation is 46.2 percent, an increase of 31.9 percentage points. Job creation reduces the official income poverty rate by 3.4 percentage points. It also reduces the LIMTIP measure by an additional 3.4 percentage points compared to the direct impact of ECE expansion. Including the impact of access to ECE services, the LIMTIP poverty rate of employed women with small children is reduced by 5.9 percentage points overall

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[2] The study of Ghana and Tanzania also assesses the impact of road improvements on commuting time, as well as employment, income, and consumption expenditures.

(to 63.3 percent), which represents about 487,000 women escaping income poverty. Our empirical results show that the employment creation achieved through increased social care spending reduces gender employment gaps, while also helping to alleviate time- and income poverty.

2. Policy Intervention

In identifying the scope for the proposed childcare expansion intervention, we follow the fifth-year goals put forward by the authors of the study as described in Table 1, below (ONU Mujeres 2021). The first and last column are from the table captioned "Síntesis de resultados del sistema de cuidados infantiles" in the report (ONU Mujeres 2021, p. 4). The enrollment rates in the second column are those as measured in the *Encuesta Nacional de Uso de Tiempo* for 2019 (ENUT 2019), while those in the third column are those as measured in the *Encuesta Nacional de Ingresos y Gastos de Hogares* for 2020 (ENIGH 2020).

Table 1 Enrollment Rates in Early Childhood Education by Age Group, Reported, Measured in ENUT 2019, ENIGH 2020, and Goal

	Enrollment Rates (%)			
Age groups	ONU Mujeres 2021	ENUT 2019	ENIGH 2020	Policy Goal (%)
0-2 years old	4	10	NA	66
3 years old	47	44	37	80
4 years old	92	85	83	100
5 years old	97	96	96	100

Source: Columns 1 & 4, ONU Mujeres 2021; columns 2 & 3 author's calculations.

The proposed intervention is to raise the enrollment rate for children aged 0–2 years to 66 percent, for 3-year-old children to 80 percent and for 4-5-year-old children to 100 percent. We expect that increased availability of childcare will be taken advantage of by households with very young children. Consequently, a reallocation of time by the members of such households ("beneficiary households") is very likely to emerge. The reallocation would affect not only the time spent on childcare but also several other tasks of household production, given their interdependence (Suh and Folbre 2015). Past research provides a cautionary tale, however. The impact on total weekly hours of household production of the use of childcare services is more important in terms of supervisory care, which is often a secondary activity undertaken by caregivers while they are performing other types of unpaid work in the household. Childcare services will not reduce the amount of time spent on the latter and so the overall measured impact may be low in terms of reduction in time spent on household production work (Folbre et al. 2005). In addition, the proposed intervention would expand employment in the Mexican economy, especially in care services. This occupation is more likely to employ women, so we expect to see an increase in the employment of women and a reduction of poverty as measured by the official poverty thresholds. This is precisely where the LIMTIP framework becomes crucial for understanding the full impact of these shifts. While the increased engagement in paid employment is likely to increase the income of households with recipients of the new jobs, those households are also likely to see an increase in time deficits and time poverty as a result. Whether the increased income is sufficient to bring poor households out of poverty and prevent non-poor households from falling into poverty as a result of the increased time deficits is an empirical question that we address in our discussion of the total impacts of the policy intervention.

3. Data & Methodology

Data

The base data set we use is the ENIGH for 2020 produced by INEGI. The ENIGH is a nationally representative survey that contains individual records and household records representing 126,838,467 individuals in 35,749,659 households. While the ENIGH does include some questions about individuals' time use, the data is insufficiently detailed and representative to allow us to produce reliable estimates of time and income poverty. We therefore augment the ENIGH with information from the ENUT for 2019, via a statistical matching procedure discussed in the next section. The ENUT is a nationally representative survey that contains individual records and household records representing 107,906,125 individuals (aged 12 and up) in 40,133,850 households. In addition, we use the *Encuesta Nacional de Ocupación y Empleo* (ENOE) for 2020 for wage data to estimate replacement costs of deficits in household production.

Statistical Matching

The ENIGH and ENUT are combined to create a synthetic file using constrained statistical matching (Kum and Masterson 2010). The purpose of the technique is to transfer information from one survey (the 'donor file') to another (the 'recipient file'). The transferred information, in this case time use data, is missing in the recipient file but necessary for research purposes. Each individual record in the recipient file is matched with a record in the donor file, where a match represents a similar record, based on several common variables in both files. The variables are hierarchically organized to create the matching cells for matching procedure. The categorical variables that we consider to be of the greatest importance in designing the match are called strata variables. For example, if we use sex and employment status as strata variables, this will mean that we would match only individuals of the same sex and employment status. With the strata variables we construct matching cells, which contain records from each file that share the characteristics represented by the strata variables. Within the cells, we use a number of variables of secondary importance as match variables. The matching progresses by rounds in which strata variables are dropped from matching cell creation in reverse order of importance.

The matching is performed on the basis of the estimated propensity scores derived from the strata and match variables. In this construction of the propensity scores, we assign weights to the coefficients of match variables, as well as strata variables not used in a particular matching round. These weights help to sort the records within a matching cell so that, for example, we match donor records with less than a primary education with recipients of a similar level of educational attainment. For every recipient in the recipient file, an observation in the donor file is matched with a donor record based on the rank of their propensity scores. The quality of match is evaluated by comparing the marginal and joint distributions of the variable of interest in the donor file and the statistically matched file (see Appendix A for a detailed description of the method and results of the statistical match).

4. Measuring time and income poverty

The methodology for implementing our measure of time and income poverty has been comprehensively documented elsewhere (see, for example: Zacharias 2017; Zacharias, Antonopoulos, and Masterson 2012; Zacharias, Masterson, and Memis 2014), therefore we give only a brief overview here. We first present the theoretical basis of the method, then proceed to the practical questions of how we estimate the required thresholds and parameters.

We begin with the basic accounting identity of time allocation which states that the physically fixed number of total hours equals the sum of time spent on income-generation, household production, personal care, and everything else which we denote as 'leisure/free-time.' Assuming the unit of time to be a week, we can write:

$$168 \equiv L_i + U_i + C_i + V_i$$

In the equation above, L_i denotes the time spent on income-generation (wage or own-account employment) by individual i, U_i the time spent on household production, C_i the time spent on personal care, and V_i the time available as 'free time.' The time deficit equation is derived from this identity by replacing the variables with the threshold values for personal care and household production, and commuting time:

$$X_{ij} = 168 - M - \alpha_{ij} R_j - D_i\left(C_{ij} + L_{ij}\right)$$

The time deficit faced by the working-age individual i in household j is represented by X_{ij}. The minimum required time for personal care and nonsubstitutable household activities is represented by M. The amount of substitutable household production time that is required to subsist with the poverty level of income is denoted by R_j. If the household is at the poverty level income, then, in order to attain the poverty level consumption, it has to spend a certain number of hours in household production activities, conditional on its characteristics. This amount varies across households according to household composition and location. The parameter α_{ij} is the share of an individual in the total time that their household needs to spend in household production to survive with the poverty level of income. Finally, the time spent on income generating activities is represented by the expression $D_i\left(C_{ij} + L_{ij}\right)$, with D_i representing an indicator that the individual i is engaging in income generating activities, C_{ij} representing the threshold for commuting time (which varies based on full-time/part-time status and rural/urban location) and L_{ij}, the time spent on the income generating activities themselves.

The difference between the total hours in a week and the sum of the minimum required time that the individual has to spend on personal care and household production is the notional time available to them for income-generation and 'leisure.' We have defined time deficit/surplus accruing to the individual as the difference between hours of income-generating activity and the notional available time. To derive the time deficit at the household-level, we add up the time deficits of the n individuals in the household:

$$X_j = \sum_{i=1}^{n} \min(0, X_{ij})$$

We do not add time surpluses, since we do not observe household members with time surpluses doing extra work to help those with time deficits. If the household has a time deficit, i.e., $X_j < 0$, we assume that the household does not have enough time to perform the required amount of substitutable household production to reproduce itself. If we assume that the time deficit can be compensated by market substitutes, the natural route is to assess the replacement cost. The latter can then be added to the income poverty threshold to generate a new threshold that is adjusted by time deficit:

$$y_j^o = \bar{y} - min\left(0, X_j\right) p$$

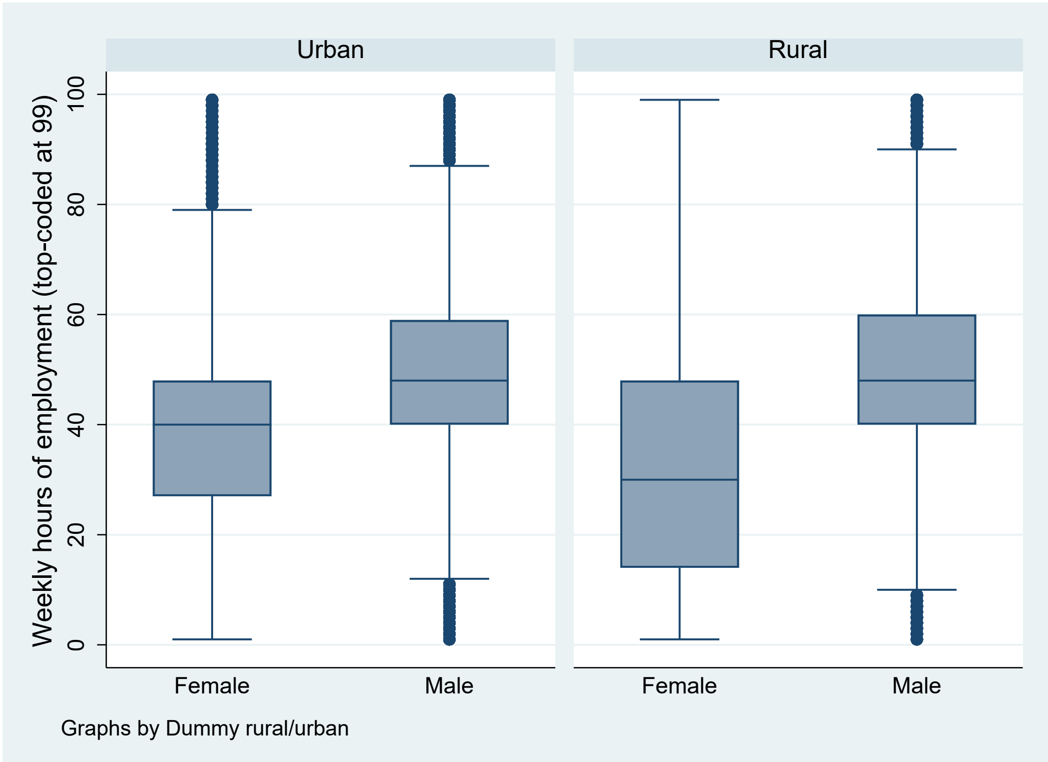
where y_j^o denotes the adjusted threshold, $\bar{y}$ the standard threshold, and p the unit replacement cost of household production. The standard and modified thresholds coincide if the household has no time deficit.

The thresholds for time allocation and modified income threshold together constitute the LIMTIP. We consider the household to be income-poor if its income is less than its adjusted threshold, and we term the household as time-poor if any of its members has a time deficit. We classify individuals as income-poor if the income of the household that they belong to is less than the adjusted income threshold, and we designate them as time-poor if they have a time deficit. The LIMTIP allows us to identify the 'hidden' income-poor—households with income above the standard threshold but below the modified threshold—who would be neglected by official poverty measures and therefore by poverty alleviation initiatives based on the standard income thresholds. By combining time and income poverty, the LIMTIP generates a four-way classification of households and individuals: (a) income-poor and time-poor; (b) income-poor and time-nonpoor; (c) income-nonpoor and time-poor; and (d) income-nonpoor and time-nonpoor.

Estimating time deficits

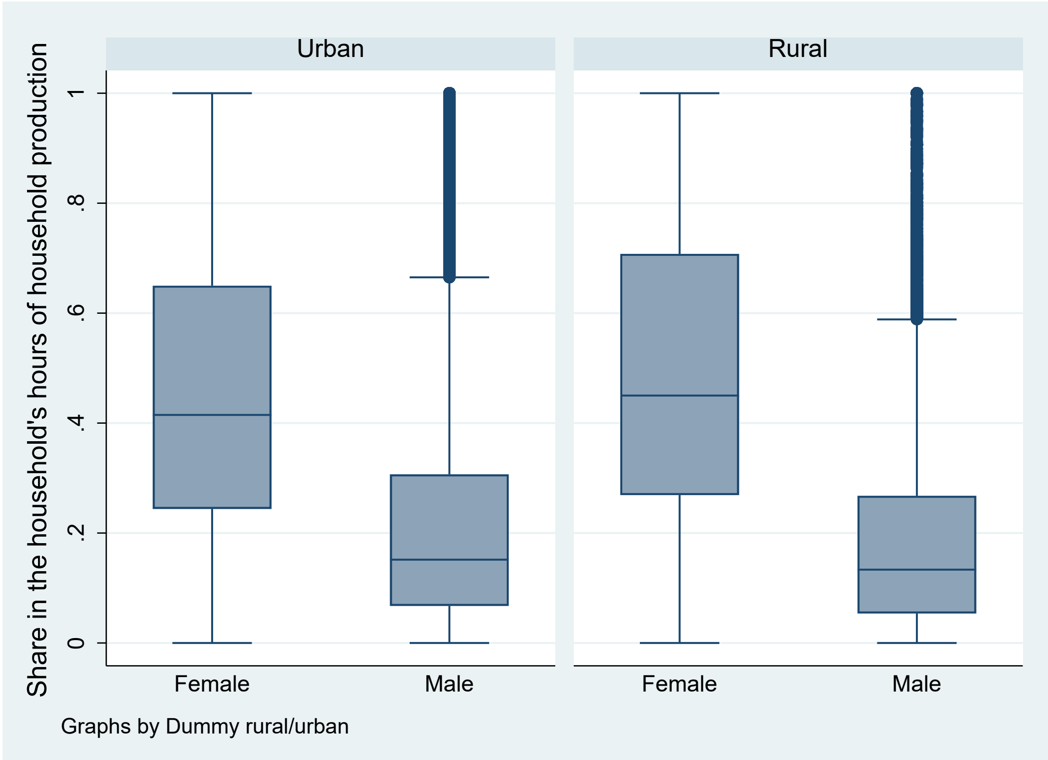
We estimate time deficits (see equation (2) above) for all individuals aged 18 to 74 years. In order to calculate time deficits for individuals in the synthetic file, we need to estimate the minimum required time for personal care and nonsubstitutable household activities (M), the thresholds for commuting time (C_{ij}), the required hours of substitutable household production time (R_j), the share of each individual of their household's required hours of household production (α_{ij}), and the usual hours of time spent on income generating activities of each individual (L_{ij}). Of these, the last is directly provided in the ENIGH. Figure 1, below, shows the distribution of weekly hours spent on income-generating activities by area of residence and sex. We can see that in both rural and urban areas, male workers spend more time on income-generating activities than their female counterparts. In each case the inter-quartile range (IQR) for men is between 40 and 60 hours per week. While the 75th percentile for women, 48 hours per week, is the same as the median for men in both rural and urban areas, women in the rural areas spend significantly fewer hours at the 25th percentile (14 versus 27 hours per week) and the median (30 versus 40 hours per week) than their urban counterparts.

Figure 1 Weekly Hours of Employment for Adults, by Area of Residence and Sex



For α_{ij}, we use the individual's share of household production time observed in the synthetic file as a proxy. Figure 2, below, shows the average shares of household production time by sex and area of residence. As expected, women's shares are much higher than men's and this gap is more pronounced in rural than urban areas. In fact, in the rural area, men's IQR is below that of women's: women's 25th percentile share is 26.9 percent, while men's 75th percentile share is 26.8 percent. The mean share for women (men) is lower (higher) in urban than in rural areas, so the gap in mean shares is 22.1 percentage points in urban areas, versus 28 percentage points in rural areas. The methods used for arriving at the remaining parameters are as follows.

Figure 2 Shares of Required Household Production Time by Area of Residence and Sex



The minimum required weekly hours of personal care were estimated as the sum of minimum necessary leisure (assumed to be equal to 10 hours per week) and the weekly averages (for all individuals aged 18 to 74 years) estimated directly from the ENUT, separately for urban and rural individuals, for the following activities: sleep; eating and drinking; hygiene and dressing; and rest. We assumed that weekly hours of nonsubstitutable household activities (e.g., managing household affairs, supervising hired help etc.) were equal to 7 hours per week in line with earlier literature (see Vickery 1977, 46). The resulting estimates are shown below in Table 2. The line labelled 'Total' is our estimate of the parameter M in equation (2) above.

Table 2 Thresholds of personal care and nonsubstitutable household activities

	Urban	Rural
Personal maintenance		
Sleep	54	58
Eating and drinking	9	8
Hygiene and dressing	6	6
Rest	2	2
Necessary minimum leisure	10	10
Nonsubstitutable household activities	7	7
Total	88	91

Source: Authors' calculations using ENUT 2019

For the commuting time we calculated the average hours spent per week of individuals engaged in income-generating activities in urban and rural areas, separately for part-time and full-time workers. We defined full-time work as thirty-five hours per week or more spent on income-generating activities (not including time spent commuting). We used the ENUT data for the calculation, since it contained all the information required to estimate commuting time. The thresholds for commuting time are reported in Table 3, below.

Table 3 Thresholds of commuting time for individuals engaged in income-generating activities

	Commuting Time	
	Part Time	Full Time
Urban	2.9	6.4
Rural	3.0	5.7

Source: Authors' calculations using ENUT 2019

The thresholds for required household production time are defined for the household and, in principle, represent the average amount of household production that is required to subsist at the poverty level of income. The reference group in constructing the thresholds consists of households with at least one nonemployed, non-disabled adult and income around (between 75 and 150 percent) the official income poverty line. Our definition of the reference group is motivated by the need to estimate the amount of household production implicit in the official poverty line. Since poor households in which all able-bodied adults are employed may not be able to spend the amount of household production implicit in the official poverty line, we excluded such households from our definition of the reference group.

We estimate thresholds for required hours of household production using a non-linear regression method that allows for economies of scale and differences in household structure according to the age of its members.

$$time_j = a_0(N_0 + a_1 N_1 + a_2 N_2 + a_3 N_3)^d$$

The dependent variable is total weekly hours of household production, and the independent variables are the number of adults aged 18 to 64 in the household (N_0), the number of children aged 0 to 6 in the household (N_1), the number of children aged 7 to 17 in the household (N_2), and the number of adults aged 65 and up (N_3). We estimated the thresholds directly from the time use survey because the survey contained enough information (time use for all individuals in the households and reasonably good information on income for households) to identify the reference group. The estimates were obtained separately for urban and rural areas.[3] The results are presented in Table 4, below.

[3] Note that the population of households contained in Figure 1 excludes those households with more than 3 adults or children, for presentation purposes.

Table 4 Non-Linear Regression Results

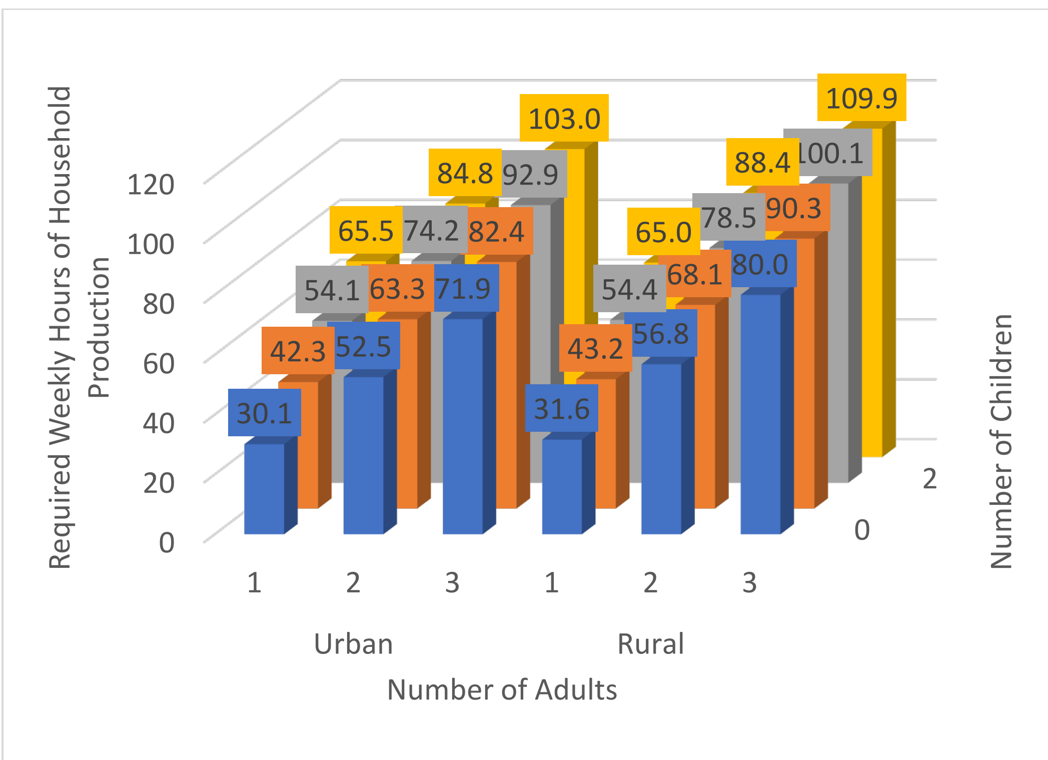
	Rural	Urban
a0	31.91*** (1.319)	29.43*** (1.143)
a1	0.533*** (0.063)	0.601*** (0.057)
a2	0.419*** (0.060)	0.555*** (0.044)
a3	0.977*** (0.071)	1.083*** (0.051)
d	0.843*** (0.033)	0.808*** (0.028)
N	1607	4113

Standard errors in parentheses

* p<0.1,** p<0.05, *** p<0.01

Using the parameters from our non-linear regression model, we can then predict the thresholds for households in the synthetic file. Figure 3, below, shows the resulting average threshold hours for households by number of children and adults (up to three in each case, for presentation purposes) and area. As is expected, the thresholds are increasing in both the number of children and number of adults.

Figure 3 Average Threshold Weekly Hours of Household Production by Number of Children, Number of Adults, and Location



Adjusting poverty thresholds

Once the above thresholds were estimated, time deficits could be calculated for each individual and then for households. In order to convert time deficits from weekly hours to monthly pesos, we employed a replacement cost method, described below.

For the replacement cost for household time deficits, we use the mean hourly wage for domestic workers. This is calculated using the three available quarterly rounds of the *Encuesta Nacional de Ocupación y Empleo* (ENOE) for 2020.[4] For our purposes, we identified domestic workers as those reporting that they work as paid domestic workers.[5] We deflate for the month of the interview and differentiate the replacement cost by urban and rural areas. The mean wage for domestic workers in 2020 was 39.32 pesos per hour in urban areas and 30.09 pesos per hour in rural areas.

Accounting for hired domestic help

Households meet their household production needs using hired domestic help, as well as their own labor. In the ENUT, we find that about 10.5 percent of all households in Mexico used hired domestic help. We need, therefore, to account for hired domestic help in our estimates of LIMTIP, both in terms of the time and income effect of hiring domestic servants.[6] We included the hours of domestic help in deriving the threshold hours of household production. Domestic servants, of course, cost money, and therefore represent a drain on the income available to the household for other expenditures. This expense needs to be considered in gauging the income poverty status of households.

We employed an intuitive and simple method based on an assessment of how much hired help contributes to meeting the threshold hours of household production. Obviously, if the household did not hire any domestic help, the contribution is zero and no adjustment needs to be made to its income. This is also the case if the total hours spent by the household members equal or exceed the threshold hours of household production. Those households in which hired help did contribute toward completing the required hours of household production, we took as the amount of contribution the minimum of (a) the difference between the threshold hours and the household's own hours and (b) the hired hours. Denoting R_j^* as the contribution, R_j^o as the 'own' hours of household production and R_j^h as the hired hours of domestic help, we can write:

$$R_j^* = 0 \text{ if } R_j^o \geq \bar{R}_j \text{or } R_j^h = 0$$

$$= \min\left(\bar{R}_j - R_j^o, R_j^h\right) \text{ otherwise}$$

We used the hourly wage of domestic workers in the urban and rural areas (see above), depending on the household's location, to calculate the expenditures for R_j^* and deducted the expenditures from the household's income. In the LIMTIP, the adjusted measure of household income was employed to determine the household's income poverty status.

[4] The ENOE was unavailable for download for the fourth quarter of 2020.

[5] Clasificación de la población ocupada port ipo de unidad económica was 'Trabajo doméstico remunerado'.

[6] Note that although this hired help was included in the calculation of household production thresholds, less than one quarter of one percent of households in the reference group hired in any help.

5. Patterns of time and income poverty

Time and Income Poverty of Individuals

Time poverty will be felt more heavily by those that are employed in income-generating activities, as can be seen in Table 5, below. Just over one quarter of adults in Mexico are time poor, but that share increases to more than one third when we consider just those that are employed. Women are slightly less likely to be time poor than men, overall. However, both employed and non-employed women have higher rates of time poverty than men. This seeming paradox is due to the fact that employment rates are higher for men than women, as discussed above. When we restrict the sample to the employed, women's time poverty rate is nearly 50 percent, 14.6 percentage points higher than that of employed men. While just 0.1 percent of non-employed men suffer time deficits, 1.9 percent of their female counterparts do. Overall, 2 percent of the time poor are not employed. Thus, in the rest of this chapter, we analyze the incidence of time and income poverty with a focus on employed individuals.

Among individuals in households with young children (under age 6), time poverty is even higher. Women's overall time poverty rates are lower than that of men, by 2.2 percentage points. The gap has increased overall because women's employment rate drops from 52.2 percent overall to 50.4 percent in households with young children, while men's employment rate increases from 80.9 percent to 89.2 percent. Nonemployed women in households with young children experience time poverty at more than twice the rate of nonemployed women in general. The same is true for nonemployed men, but the time poverty rate for nonemployed men in households with young children is just 0.3 percent, compared to 4.5 percent for women. Employed men and women in households with young children have higher rates of time poverty than employed individuals generally, but the increase is larger for women (7.6 percentage points, to 53.8 percent) than for men (3.8 percentage points, to 35.4 percent). Thus, the gender gap in time poverty rates among employed persons rises to 18.4 percentage points when looking just at households with young children. This is clear evidence of the additional burden of responsibility for household production work that the presence of young children places on women, employed or not.

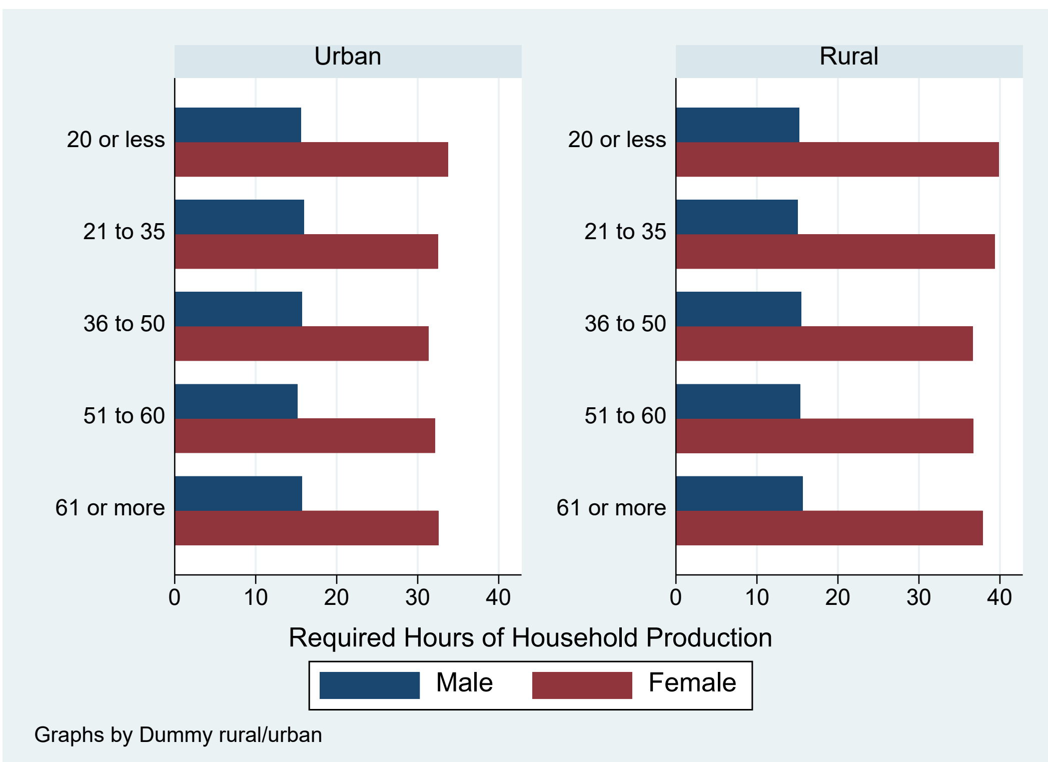
Table 5 Incidence of Time Poverty by Sex, Employment Status and Presence of Young Children of Individuals Aged 18 to 74

	Female		Male	
	Time Poverty Rate (percent)	Number of Time Poor (millions)	Time Poverty Rate (percent)	Number of Time Poor (millions)
Not employed	1.9	0.4	0.1	0.0
with young children	4.5	0.3	0.3	0.0
Employed	46.2	10.7	31.6	10.3
with young children	53.8	3.9	35.4	3.7
Total	25.0	11.2	25.6	10.3
with young children	29.4	4.2	31.6	3.7

The reason that employed women are more likely to be time poor is that they are expected to do more of the household production work than employed men irrespective of how many hours they spend on employment. Figure 4 demonstrates this phenomenon. There is very little variation for employed men in terms of their weekly hours of required household production as hours of employment changes: the average ranges between 15 and 16 hours per week in both urban and rural areas. For women there is a 2-to-3-hour decline in hours of required household production between working less than 20 hours and working full time (36 to 50 hours per week spent on income generating activities). But whether they work full-time or part-time in income-generating activities, they work another full-time job at home as well.

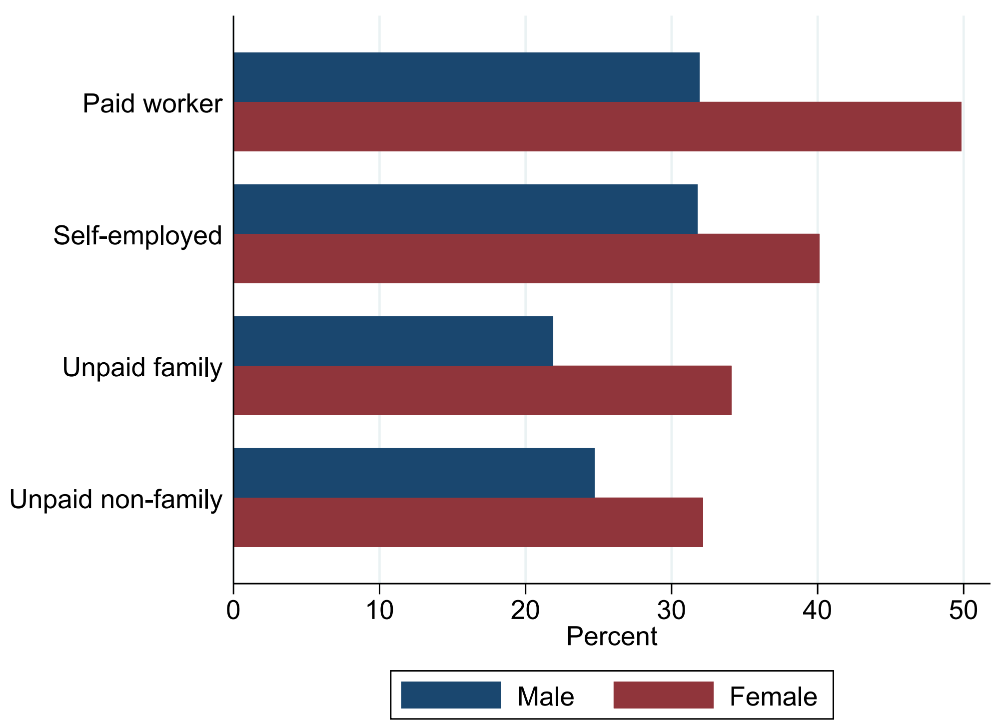
This pattern is more pronounced in rural areas, as we can see. Rural women's average required hours of household production is 5 to 6 hours greater than that of their urban counterparts at all levels of income-generating activity. The situation for employed women in urban areas is not much better. While those working part-time do just under 40 hours per week of required household production work, those working 36 to 50 hours on income generation also do 36.7 hours per week of household production. Thus, it is easy to see why employed women have higher rates of time poverty than employed men. Whether in rural or urban areas, employed full-time or part-time, men spend on average about 15.6 hours per week on household production work, while employed women work 30 to 40 hours in the home, no matter how much income-generating work they do.

Figure 4 Average hours of required household production, by hours of employment and sex: employed persons (Urban and Rural Mexico)



Turning to the breakdown of time poverty rates by type of employment, we can see important differences, especially for women (see Figure 5, below). Time poverty rates are highest for persons in paid employment, although self-employed men have nearly as high a rate of time poverty as those in paid employment. Within each employment category, time poverty rates are higher for women than for men. This is despite the fact that women have lower average weekly hours of employment in each category than men. The difference is largest among the self-employed, accounting for the relatively smaller gap in time poverty rates among self-employed workers. Employed women are likelier to be self-employed (27.3 versus 20.6 percent) and unpaid family workers (6.9 versus 4.3 percent) than men. While for women unpaid work carries a lower probability of incurring time poverty, the time poverty rate for women in unpaid family work is still higher than that of men in any type of work. It's clear, however, that the transition from unpaid to paid employment carries with it a higher incidence of time poverty, especially for women. This fact must temper hopes of welfare gains from paid employment for women.

Figure 5 Time poverty rates by employment status and sex



Turning to consider income poverty among the employed, we note first that the official poverty rate is 45.6 percent in Mexico, but that poverty is more widespread in rural areas (53.6 percent) than in urban areas (43.3 percent). In each case the poverty rate is higher for men than women, though the difference is smallest in rural areas (just one percentage point). By construction, time-adjusted poverty rates will be higher, since for those households with time deficits we increase the poverty threshold, while those without time deficits retain the official threshold. However, the difference between the two rates is stark. When taking time deficits into account the poverty rate for employed individuals rises to 55.3 percent, compared to the 45.6 percent official rate. We refer to the difference (9.7 percent of employed persons, or 5.4 million people, in Mexico) as hidden poverty, because while these individuals are not considered poor by the official measure, they live in households without the means to achieve the standard of living that the official poverty line represents. The rate of hidden poverty in rural areas is higher than that of urban areas (11.7 versus 9.1 percent) and higher for women than for men. This reflects the fact that employed women are more likely to suffer time deficits, which means that the households they live in will be more likely to be in hidden poverty. Nevertheless, women make up less than half of the hidden poor among employed individuals because of their lower employment rate.

Table 6 Poverty among employed persons (18 to 74 years of age): Official vs. Adjusted

	Poverty Rate (percent)			Number of poor persons (millions)		
Urban	Official	Adjusted	Hidden	Official	Adjusted	Hidden
Female	41.6%	51.9%	10.3%	7.6	9.5	1.9
Male	44.5%	52.7%	8.2%	11.1	13.1	2.0
Total	43.3%	52.4%	9.1%	18.7	22.6	3.9
Rural						
Female	53.0%	66.3%	13.3%	2.6	3.3	0.7
Male	54.0%	64.8%	10.7%	4.2	5.0	0.8
Total	53.6%	65.4%	11.7%	6.8	8.3	1.5
Mexico						
Female	44.0%	55.0%	11.0%	10.2	12.8	2.6
Male	46.8%	55.6%	8.8%	15.3	18.2	2.9
Total	45.6%	55.3%	9.7%	25.5	30.9	5.4

Combining our two dimensions of poverty gives us a four-way categorization of time and income poverty (LIMTIP) for individuals. The breakdown of employed individuals into these four categories by sex and area of residence is contained in Table 7, below. The two columns on the right additionally provide the rates of time poverty for employed individuals. Beginning with the distribution in Mexico as a whole, we note that more than 40 percent of the time-adjusted income poor individuals are time poor as well (20.9 percent of the 50.4 percent total). However, among income poor employed women, the time poverty rate is just over 50 percent. While just 18.9 percent of men are both time and income poor, 27.6 percent of employed women are. The time poverty rate of income poor women is close to 50 percent in both rural and urban areas. This means that 26.1 and 32.9 percent of employed women are both income and time poor in urban and rural areas respectively. The corresponding rates for men are 17.1 and 24.6 percent. Among employed income poor men, 32.3 and 38 percent are in time poverty in urban and rural areas, respectively. Relatively few employed individuals (29.5 percent) are untouched by either time or income poverty, but that share drops to just 18.1 percent when considering rural employed women. At the other end of the spectrum, 34.4 percent of employed urban men are neither time nor income poor.

Table 7 Distribution of employed persons (18 to 74 years of age) by LIMTIP and incidence of time poverty

	LIMTIP Classification of Individuals				Time Poverty	
	Income-poor and time-poor	Income-poor and time-nonpoor	Income-nonpoor and time-poor	Income-nonpoor and time-nonpoor	Nonpoor	Poor
Urban						
Female	26.1%	25.8%	19.4%	28.7%	40.3%	50.3%
Male	17.1%	35.7%	12.9%	34.4%	27.3%	32.3%
Total	20.9%	31.5%	15.7%	32.0%	32.9%	39.9%
Rural						
Female	32.9%	33.3%	15.6%	18.1%	46.4%	49.7%
Male	24.6%	40.1%	12.1%	23.1%	34.4%	38.0%
Total	27.8%	37.5%	13.5%	21.2%	38.9%	42.6%
Mexico						
Female	27.6%	27.4%	18.6%	26.5%	41.3%	50.2%
Male	18.9%	36.7%	12.7%	31.7%	28.6%	33.9%
Total	22.5%	32.9%	15.2%	29.5%	33.9%	40.6%

Time and Income Poverty among Households

In this section, we consider the time and income poverty of employed households, which we define as those households in which the head or their spouse are employed in income-generating activities. We first compare the incidence of official and time-adjusted poverty. Though the thresholds are for equivalized per capita household income, income poverty is measured at the household level in Mexico. So, the official and time-adjusted poverty rates for employed households will necessarily be similar to those of employed persons. As shown in Table 8 below, the official poverty rate among employed households in Mexico is 46.6 percent, though in rural areas it is much higher (54.1 percent). The time-adjusted rate follows the same regional pattern, with rural poverty (64.7 percent) much higher than the urban rate (52.4 percent) as well as the overall rate (55.1 percent). Hidden poverty includes 8.5 percent of all employed households, 10.5 percent of rural, and 7.9 percent of urban employed households. There are 14.6 million employed households that are officially poor in Mexico, but an additional 2.7

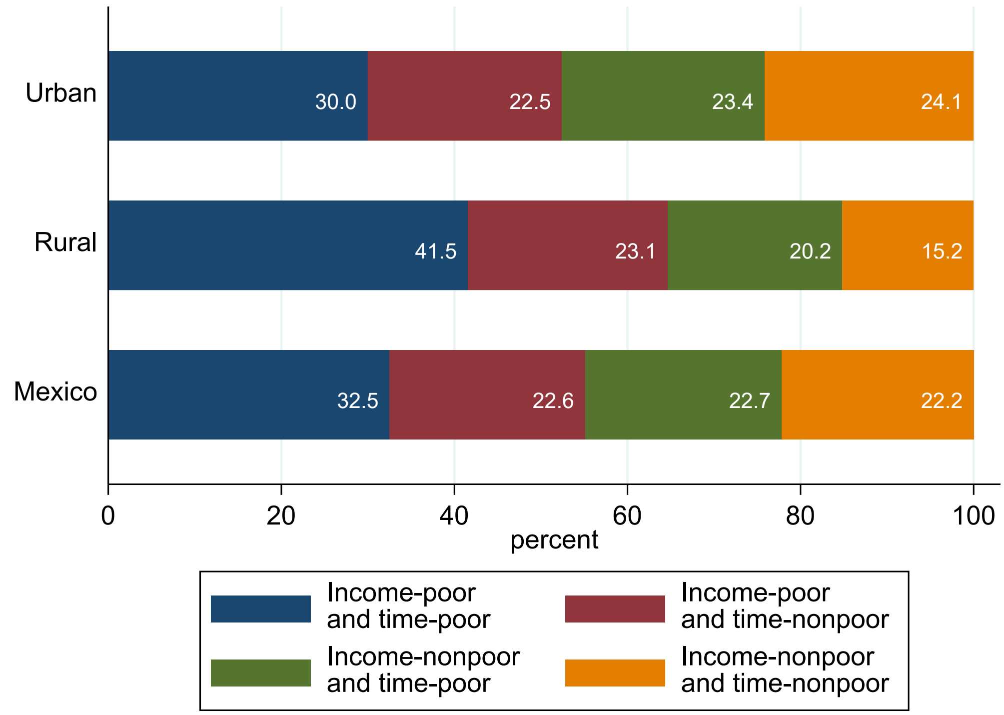
million are in hidden poverty. Of the latter, most (1.9 million) are in urban areas, while an additional 0.7 million are in rural areas. This widespread incidence of hidden poverty implies high rates of time poverty for employed households in Mexico, as we will now demonstrate.

Table 8 Poverty among employed households: Official vs. adjusted

	Poverty Rate (percent)			Number of poor households (millions)		
	Official	Adjusted	Hidden	Official	Adjusted	Hidden
Urban	44.5%	52.4%	7.9%	10.9	12.8	1.9
Rural	54.1%	64.7%	10.5%	3.7	4.4	0.7
Total	46.6%	55.1%	8.5%	14.6	17.3	2.7

In Figure 6, below, we see the breakdown of employed households in rural and urban areas into our four-way classification on time and income poverty. Recall that for a household to be considered time poor, one or more persons within the household must be time poor. Remarkably, over half of poor employed households are both time and income poor (32.5 of 55.1 percent). The share of income poor rural households that is not time poor is a little larger than the overall share or that among employed urban households (23.1 versus 22.6 and 22.5 percent, respectively). However, the share of employed rural households that is both time and income poor is 41.5 percent. A higher share of urban than rural employed households are time poor but not income poor (23.4 versus 20.2 percent), despite their lower overall rate of time poverty (53.4 versus 61.7 percent). Just 15.2 percent of employed rural households face neither time nor income poverty, while 24.1 percent of employed urban households do.

Figure 6 Distribution of employed households by LIMTIP category and area of residence



Employed adults in Mexico face high rates of both time and income poverty. This implies that the conditions of employment (pay and hours) as well as the institutional structures around the social provision of care are inadequate to enable most Mexicans to achieve a nominal standard of living. The widespread incidence of both time and income poverty in employed households in Mexico reinforces this conclusion. These observations make the case for investment in social infrastructure such as universal provision of early childhood education like those being considered in this study. The patterns of time and income poverty, especially among employed women, indicate that more may be needed to address the underlying issues. In the next section, we report estimates of the direct impact of increased access to early childhood education services on time use as well as on time and income poverty in Mexico.

6. Simulation of Impacts on Time Use

In assessing the impact on time allocation, we construct statistical models of the impact of ECE enrollment using the ENUT data, which provides enrollment information for young children. We estimate separate models for each of the four policy target age groups (children aged 0 to 2, 3, 4, and 5 years). We know that the average time spent on household production is markedly different between the sexes, with girls and women spending more time on average than boys and men. It is reasonable to expect that the responsiveness of the time spent on household production to the increased availability of ECE will differ systematically among these groups based on sex and age.

To control for a variety of confounding factors that affect time spent on household production for individuals, we estimated separate Tobit models for girls, boys, women, and men in urban and rural areas. The results of the regressions are reported in Appendix B, Tables B1 and B2. We used a rich set of controls to estimate the impact of young children's enrollment in ECE on time use. In addition to the standard age and education characteristics, we also include controls for job characteristics, marital status, proxies for household bargaining structure (including relative age between husband and wife, and relative education), household size and composition, household income, and access to public services (e.g., electricity). Using these models, we predict household production hours for boys, girls, men, and women in households with young children with and without all children in each of the four age groups enrolled.

To identify beneficiaries, we follow two procedures. Since the target enrollment for children aged 4 and 5 is 100 percent, all such children are enrolled in the simulation. We assign households with younger children that are not already enrolled to be beneficiaries by their predicted likelihood of enrolling their children (see Appendix B for a description of the procedure). In the simulation, 10.4 percent of urban households and 11.7 percent of rural households have a child enrolled as a result of the policy. For beneficiary households we multiply the actual hours of household production for each individual by one plus the predicted changes for each of the beneficiary groups (ages 0 to 2, age 3, age 4, and age 5) that that household belongs to. This produces an estimate for household production hours for each individual given the policy goal achieved. Our results show that time spent on household production is negatively correlated with the enrollment of children in preschool and childcare for each subgroup.

Table 9 shows the impact of the proposed expansion of early childhood care services on time spent on household production in households with children aged 0 to 5 years old. Before the intervention, girls and boys spent, on average, 35.0 and 12.0 hours a week on household production, while women and men spent 38.5 and 13.1 hours a week. Our model predicts that the intervention would reduce the average time spent on household production, by 5.8 and 6.8 hours for girls and women, respectively, with a smaller absolute reduction for boys and men of 2.2 and 2.4 hours, respectively. The relative reduction for men and boys was slightly larger than that for women and girls (18.5 versus 17.2 percent). The gendered impact reflects the fact that care responsibilities are currently borne mostly by girls and women.

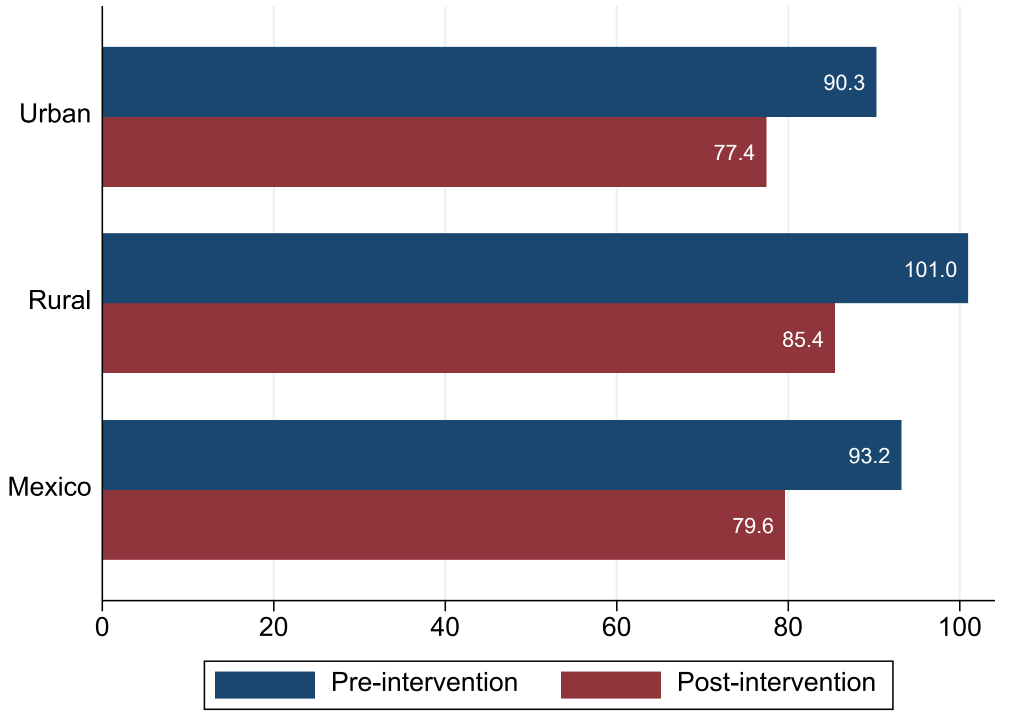
Table 9 Average Weekly Hours of Household Production for Individuals in Households with Young Children, Before and After the Intervention

	Girls	Boys	Women	Men
Baseline	35.0	12.0	38.5	13.1
With direct effects	29.1	9.7	31.7	10.7
Reduction	-5.8	-2.2	-6.8	-2.4

Source: Authors' estimates.

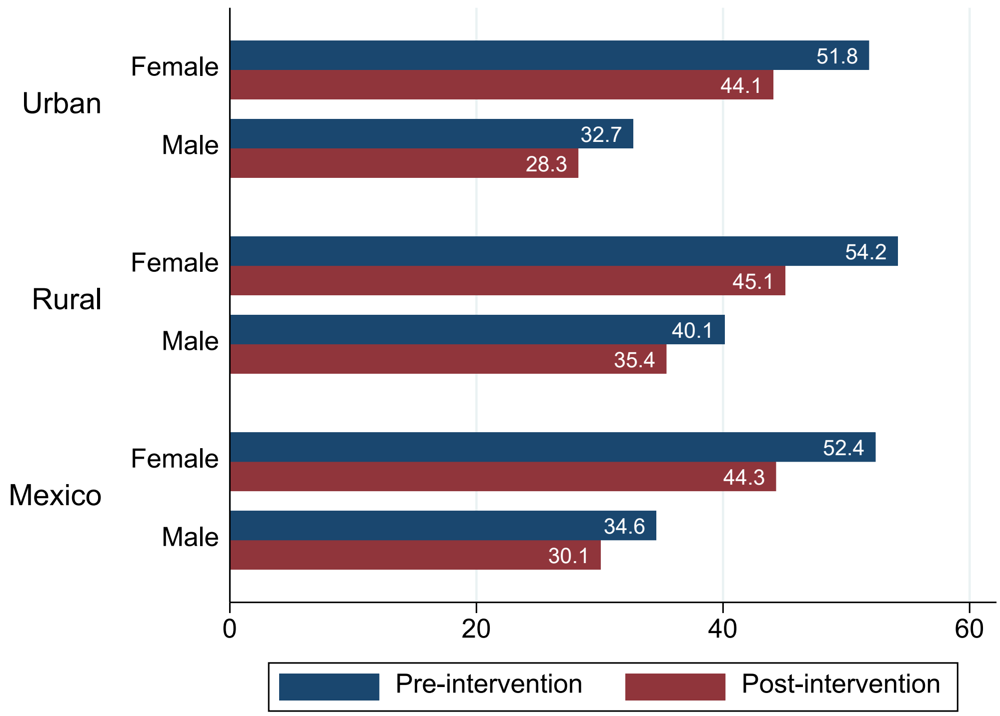
Using the new distribution of household production hours generated by the estimation of the direct effects of childhood expansion, we re-estimated the thresholds for required household production, following the same method described in Section 4. The resulting thresholds are lower for households with young children (see Figure 7, below). Thresholds for households with young children were reduced by 13.6 hours overall. The reduction is slightly larger (15.6 hours per week) in rural areas and more modest in urban areas (12.9 hours per week). The impacts on time use and thresholds for household production time were substantial and should also have a substantial impact on the picture of time and income poverty, by reducing the time deficits of those in beneficiary households. This reduction will lower time poverty rates as well as income poverty rates. The latter change is a result of the reduction in hidden poverty due to lower time deficits.

Figure 7 Effect of the Expansion of ECE on Average Thresholds of Required Household Production for Beneficiary Households by Area of Residence



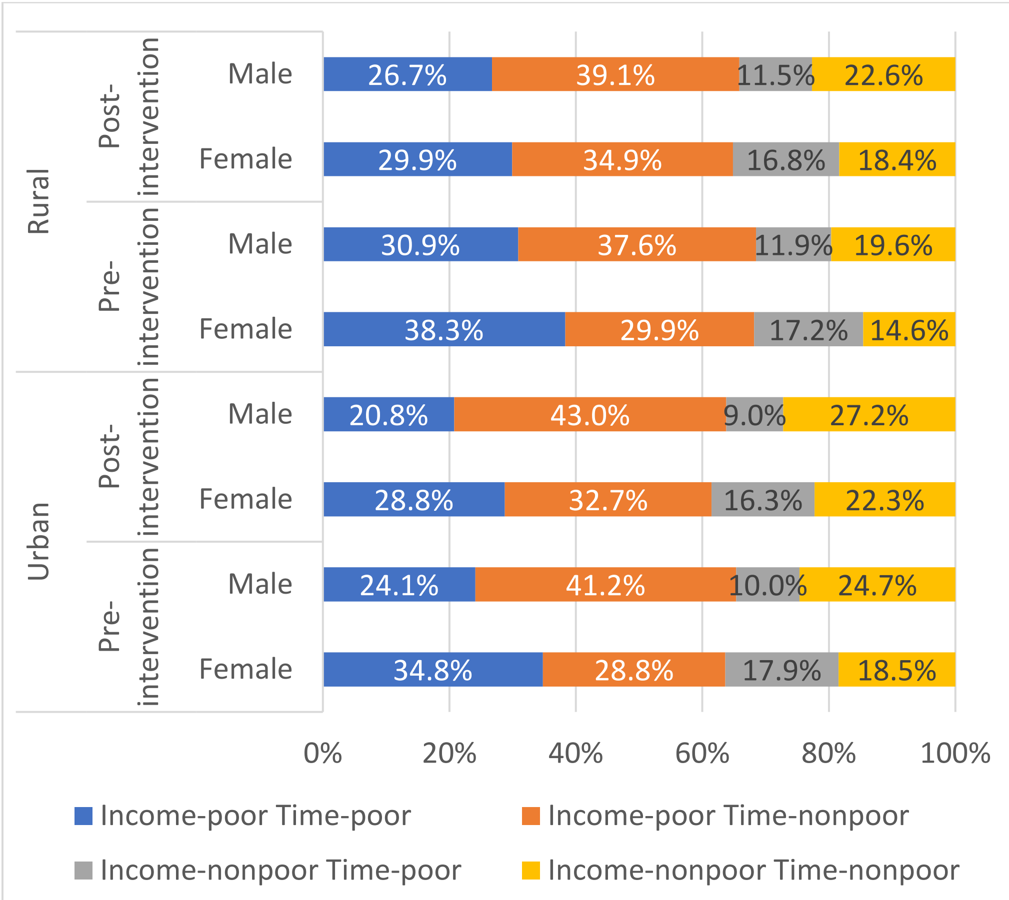
The reductions in thresholds will likely reduce time poverty rates for individuals, but because they are household-level thresholds, they may not have a significant gendered effect. There will be some small changes in individual's shares of household production in beneficiary households as well, due to the changes in their hours and because the relative change for men and boys is slightly larger, the overall trend will be to slightly worsen gender gaps in household production time, while still lowering the levels for everyone. Figure 8 below shows the time poverty rates for women and men in beneficiary households in rural and urban areas and for Mexico overall before and after the intervention. The reductions in time poverty rates for women are greater than that of men in Mexico overall (8.1 versus 4.5 percentage points), in rural areas (9.1 versus 4.7 percentage points), and in urban areas (7.7 versus 4.4 percentage points). The gender gap in time poverty rates is still large, however, having fallen only by 3.6 percentage points (to 14.2 percentage points) overall. And it is largest in the urban areas, where it also fell the least (3.3 percentage points to 15.8 percentage points). Although women's time poverty rate in beneficiary households are higher in rural areas, men's are so much higher that the gap between men and women is lower (falling 4.4 to 9.7 percentage points after the intervention).

Figure 8 Time Poverty Rates for Employed Individuals in Beneficiary Households Before and After the Policy Intervention, by Sex and Area of Residence



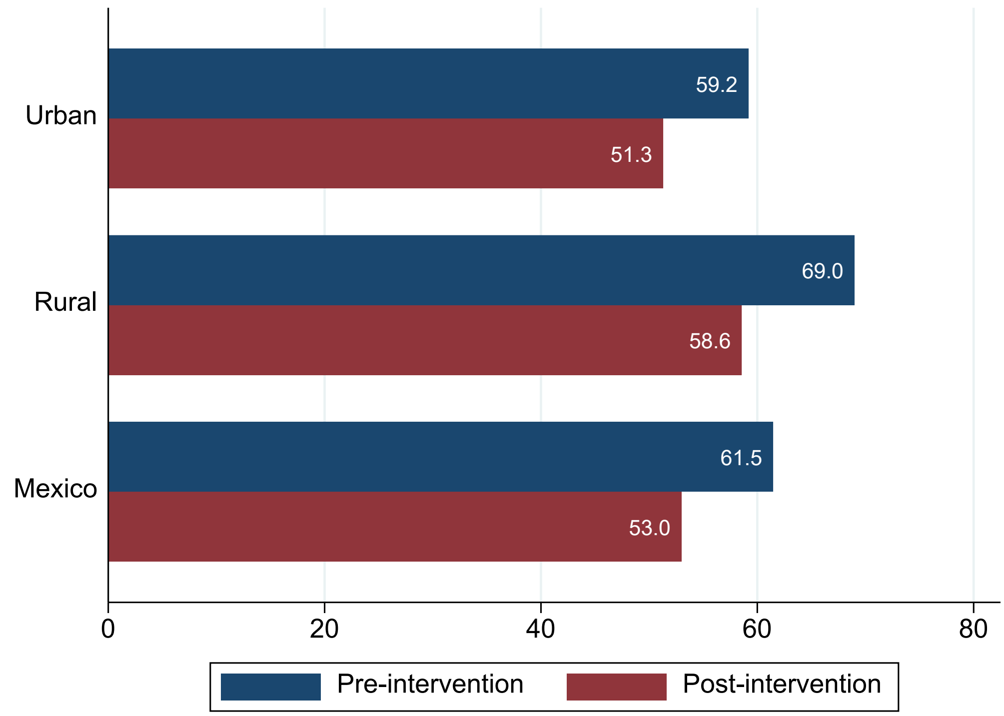
The reductions in time poverty demonstrated above translate directly into changes in our four-way classification of time and income poverty for employed persons in beneficiary households (see Figure 9, below). Because we see reductions in time deficits, there will be less hidden poverty and so lower income poverty. However, reductions in time poverty are greater than those in income poverty. Employed women in income poor beneficiary households saw reductions in time poverty of 7.8 and 10.0 percentage points (to 46.8 and 46.1 percent) in rural and urban areas, respectively, while men saw a 4.5 percentage point reduction (to 32.6 and 40.6 percent in urban and rural areas, respectively). Meanwhile the share of employed women in beneficiary households that were neither time nor income poor grew by 3.8 percentage points in both rural and urban areas. Men in both areas were still more likely to suffer neither time nor income poverty.

Figure 9 LIMTIP Classification of Employed Individuals in Beneficiary Households Before and After Policy, by Sex and Location



The reductions in time deficits will mean a reduction in time poverty rates for beneficiary households. This impact is captured in Figure 10, below, which shows the time poverty rates for beneficiary households before and after the intervention. Again, the reduction is significant. The overall time poverty rates for these households falls by 8.5 percentage points (though is still high at 53 percent). The decline is smaller in urban areas (7.9 percentage points), where time poverty rates were lower (59.2 percent), than in rural areas, where the time poverty rate fell from 69 to 58.6 percent. These results reinforce the idea that the time poverty impact of having young children is significant. Access to ECE services is predicted to make an appreciable difference for households with young children that are able to access these services.

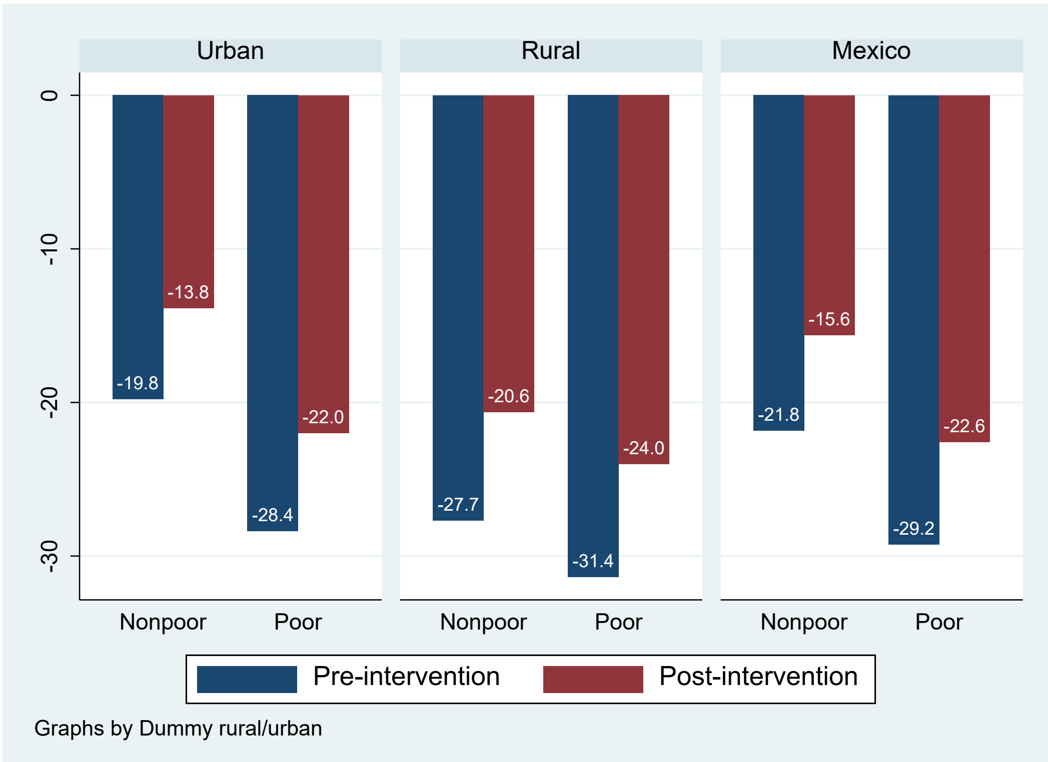
Figure 10 Effect of the Expansion of ECE on Time Poverty Rates of Beneficiary Households, by Area of Residence



The latter point is reinforced by the changes in time deficits (the depth of time poverty for individuals and households) among time poor beneficiary households (see Figure 11, below).[7] We see the same pattern by location as before, with rural time deficits being larger than urban time deficits. Indeed, rural time deficits for the nonpoor are almost as deep as those of the urban income poor. Nonetheless, there are reductions in the size of time deficits across the board. Average time deficits fell by 6.6 hours for the income poor households (6.4 and 7.4 hours in urban and rural areas, respectively) and 6.2 hours for income nonpoor households (6 and 7.1 hours, respectively for urban and rural areas). So, while these reductions are important, the time deficits remaining are still significant: 22.6 hours among income and time poor beneficiary households with the policy intervention, and 15.6 hours in income nonpoor but time poor beneficiary households.

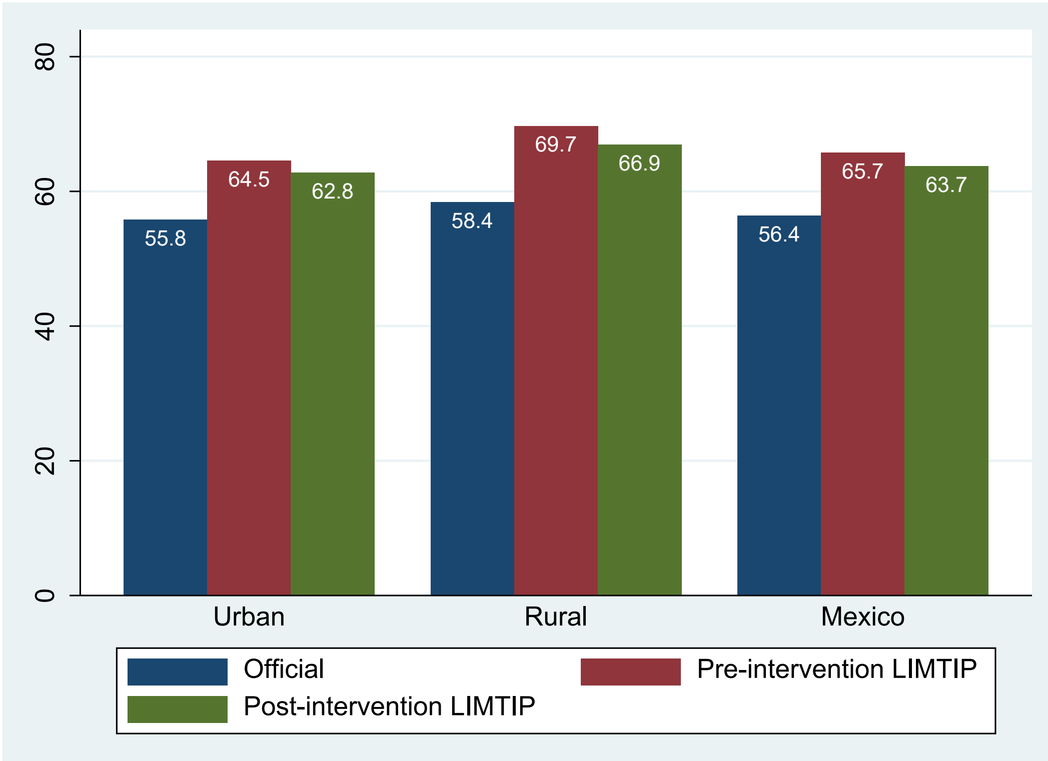
[7] Time poor here refers to the beneficiary households that were time poor prior to the application of the policy.

Figure 11 Effect of the Expansion of ECE on the Average Time Deficit per Household of Time Poor Beneficiary Households by Location and LIMTIP Poverty Status (weekly hours)



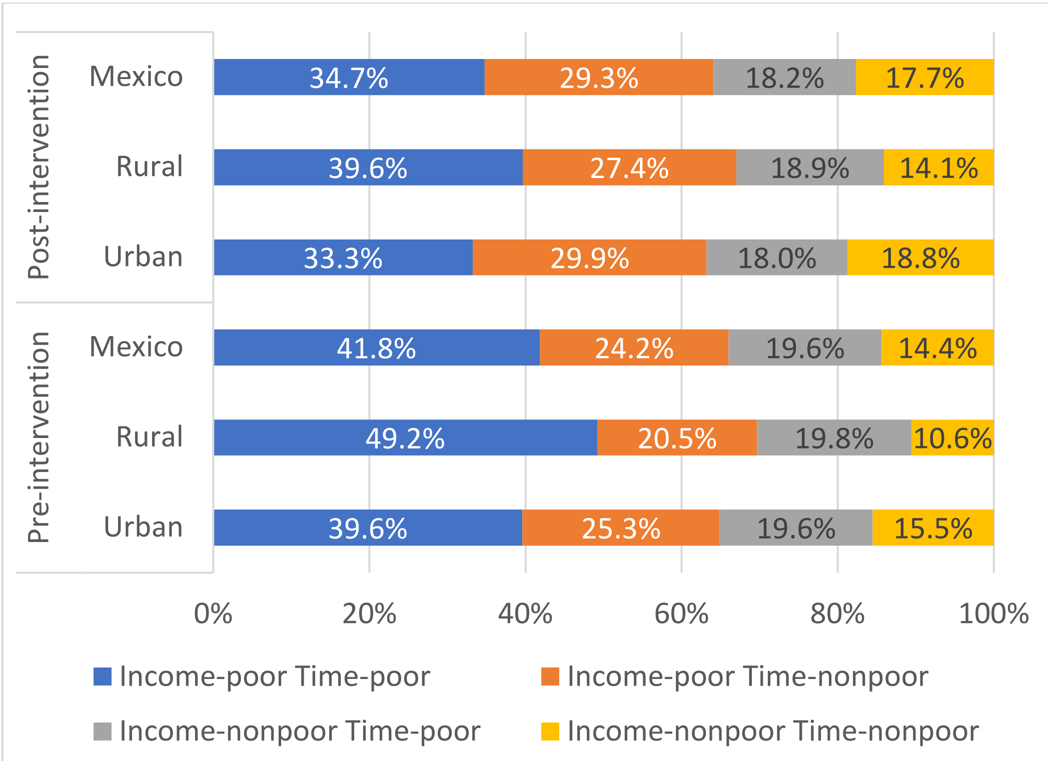
In terms of the LIMTIP measure, the expansion of ECE services will have two direct impacts due to changes in time use patterns. First, time deficits (and so time poverty) will be reduced, as we have seen above. Second, hidden poverty will be reduced because lower household time deficits mean smaller adjustments to the official thresholds for time poor households. The second impact is apparent in Figure 12, below. First note that among employed beneficiary households, headcount poverty is significantly higher than for households in Mexico overall (56.4 versus 46.6 percent). As we saw in the previous section, hidden poverty is more widespread in rural than urban areas. Our simulation predicts that the expansion of ECE services has a modest impact on hidden poverty in Mexico, reducing it by two percentage points. The reduction is slightly smaller for urban areas (1.7 percentage points) and slightly larger (2.8 percentage points) for rural areas. Still reducing hidden poverty to 7.3 percent among employed beneficiary households is progress.

Figure 12 Official, Time-adjusted and Post-intervention Time-adjusted Poverty Rates for Employed Beneficiary Households



Putting the direct time poverty and income poverty impacts of ECE expansion together, Figure 13 (below) gives us a picture of the change in the overall distribution of time and income poverty among employed households that were direct beneficiaries of ECE expansion. Time-adjusted income poverty falls by 1.9 percentage points (from 66 to 64.1 percent) while time poverty declines by 8.5 percentage points overall (from 61.5 to 53 percent). Time poverty declines more sharply (by 9.2 percentage points) among the income poor than the nonpoor (6.9 percentage points). These same patterns are repeated in the urban and rural areas, although in the latter the reductions in both time and income poverty were larger. The share of employed beneficiary households in the rural areas that were neither time nor income poor grew by 3.5 percentage points, to 14.1 percent, while the urban share grew nearly as much, to 18.8 percent.

Figure 13 Direct Effect of the Expansion of ECE on the LIMTCP Distribution of Employed Beneficiary Households by Location



In short, while the direct impact of increased access to ECE services was modest in terms of reductions in income poverty, the impacts on time deficits and time poverty were more pronounced. We speculate that this is because the main impact of ECE services is in reducing supervisory care, which is generally a secondary activity. Nevertheless, we estimate reductions in time poverty that are greater for women than for men, and reductions in time poverty rates and time deficits for households. Of course, the direct impact of ECE expansion is not the only impact that matters for time and income poverty. In the next section we report the results of the employment simulation that we did to incorporate the impacts on employment, income and time use of the expansion of ECE services on time and income poverty.

7. Simulation of Impacts on Employment

Changes in employment affect time and income poverty through diverse channels. First, the increase in income from additional earnings will enable some to escape income poverty. Second, the increased engagement with income-generating activities means greater time deficits (or smaller surpluses) all else equal. Finally, the distribution of household production responsibilities among the individuals can change as a result of the changes in their employment status, e.g., because the newly employed women wield greater bargaining power (Brines 1993). Such changes in the intrahousehold division of household production can reduce or increase time deficits of household members, depending on the specific shifts involved. The degree to which employment increases can alleviate time and income poverty depends on the structure of the labor market, especially in terms of hours and earnings. It also depends on the strength of patriarchal norms which critically shape the potential redistribution of household production requirements in the face of increased time spent by members on income-generating activities. Our simulation attempts to grapple with these factors to arrive at an empirical estimate of the effect of employment changes on time and income poverty. We provide a brief outline of the steps in our simulation below. For a fuller examination of the process outlined below, see Appendix C.

Our procedure begins by distributing the changes in employment as predicted by the input-output model in the ONU Mujeres study across occupations, using the existing occupational distribution in the ENIGH. We then identify potential job recipients and predict the likelihood of their being employed, as well as the ranking of industry and occupation that they are likely to find work in. We then use a hot-decking statistical matching procedure to assign jobs to each potential recipient in the order of their likelihood of being employed, and their likeliest industry and occupation, until all of the jobs predicted to be created are used up. Once this is done, we re-assign household production hours to all those individuals in households with job recipients, using another hot-decking statistical match. Once complete, we recompute time deficits for individuals using the thresholds calculated for the direct impact simulation above. Then we adjust income poverty thresholds as before with the new levels of household time deficits and categorize individuals and households by time and income poverty status. We report the results below.

The expansion of childcare services will naturally increase employment, especially given the labor-intensive nature of the services being provided. We should expect, therefore that employment rates will rise substantially, given the scope of the intervention. The employment created is broken down into two-digit industries in Table 10, below (for a full occupational breakdown by industry, see Table C1). The greatest number of jobs is in the *Guarderias* (Child care centers), which are the most labor-intensive and currently have the lowest enrollment rates. This falls under the 2-digit industry 62 health care and social assistance. The industry with the next largest employment gain is 23 construction, created by the building of new facilities to house the new centers.

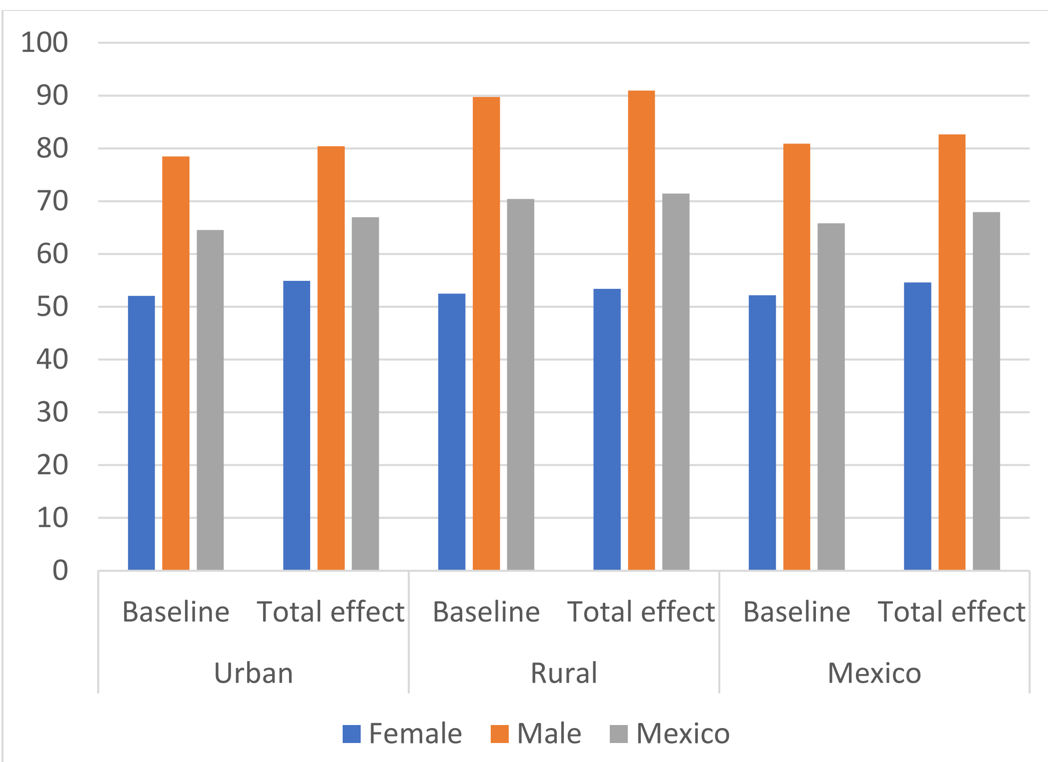
Table 10 Employment Creation by Industry

2-Digit Industry	Employment
11 Agriculture, Forestry, Fishing and Hunting	198,184
21 Mining	31,772
22 Utilities	9,390
23 Construction	871,638
31 Manufacturing - Food and Apparel	102,383
32 Manufacturing - Wood, Chemical, and Plastics	75,224
33 Manufacturing - Metal, Machinery, and Equipment	83,695
43 Wholesale trade	188,518
46 Retail trade	196,295
48 Transportation	37,756
49 Postal services and warehousing	2,949
51 Information	10,773
52 Finance and Insurance	13,669
53 Real Estate and Rental and Leasing	140,728
54 Professional, Scientific, and Technical Services	26,894
55 Management of Companies and Enterprises	1,308
56 Administrative and Support Services	113,200
61 Educational Services	157,941

62 Health Care and Social Assistance	896,139
71 Arts, Entertainment, and Recreation	13,776
72 Accommodation and Food Services	584,093
81 Other Services (except Public Administration)	115,591
93 Public Administration	12,954
Total	3,884,870

The distribution of the 3.9 million new jobs will be different by sex, since the industries that see the largest employment increases are each heavily gender-segregated. The changes in employment rates by sex and area of residence is shown in Figure 14, below. The overall employment rate for Mexico rises nearly two percentage points, from 65.8 to 67.9 percent. The increase is more noticeable in urban areas, which see a 2.4 percentage point increase (to 67 percent), while in rural areas the employment rate rises just 1.1 percentage points to 71.5 percent. Employment rates among rural adults are still nearly four percentage points higher than among urban adults. The increase in employment rate is larger for women than for men (2.4 versus 1.8 percentage points, respectively). This is driven mostly by women's employment in urban areas, where the employment rate rises from 52.1 to 54.9 percent for women, while in rural areas the increase is less than one percentage point. This difference is enough to push urban women past rural women in terms of employment, according to our simulation. Overall, in terms of employment, we estimate that the expansion of childcare services will have the greatest impact on urban women.

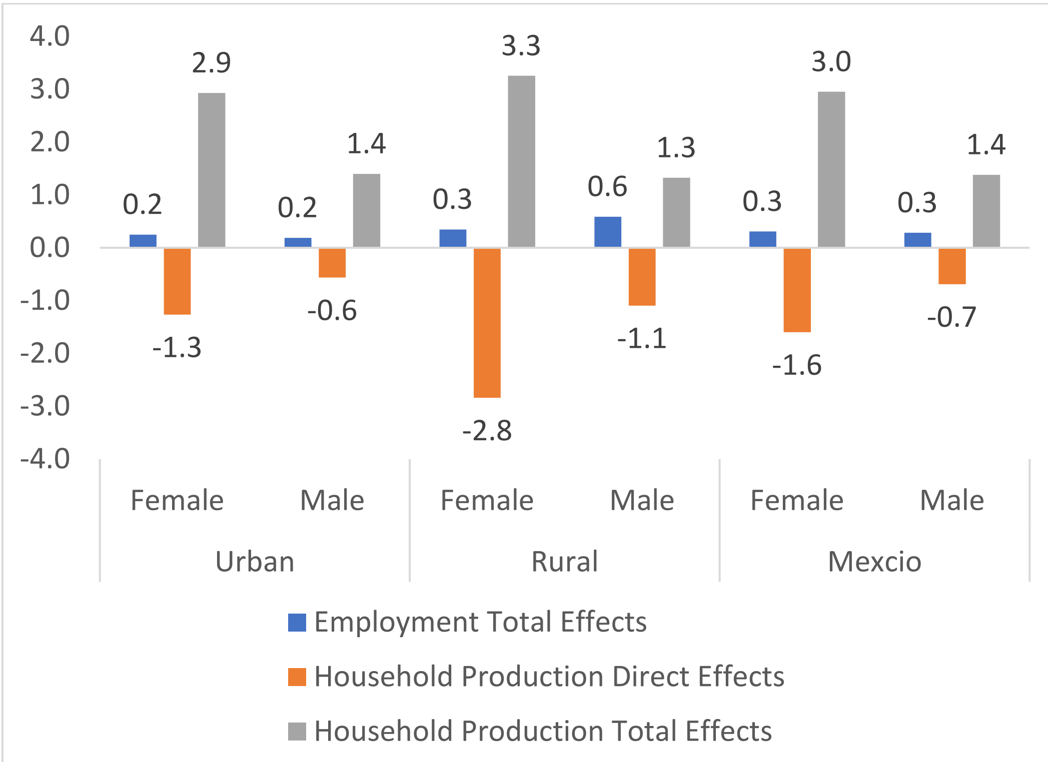
Figure 14 Employment Rate by Sex and Location of Persons 18–74 Years of Age (percent), Actual (baseline) and Total Effect



An increase in paid employment naturally implies an increase in income, but it also brings with it greater demands on the individual's time. The changes in average time spent per week on employment and household production as a result of the policy intervention is presented in Figure 15, below. Direct effects refer to the time use impact of the expansion of ECE access and total effect refers to the combination of that impact and the expansion of employment necessary for the ECE expansion. As we have observed above, employed women spend more time on household production and less on employment than men. We estimate that the expansion of childcare reduces the household production time spent by employed women in Mexico by about 1.6 hours while reducing the time spent by employed men by 0.7 hours per week. In the urban areas, employed women on average spend 1.3 hours less per week on household production after the intervention, while in rural areas the reduction for employed women is 2.8 hours per week. For men there is a smaller difference in the change in household production time spent between rural and urban areas (1.1 compared to 0.6 fewer hours per week). Taking the changes in the time spent on household production by location and gender suggests that the policy intervention, has a small direct effect on reducing the gender disparity in the division of household production responsibilities but that this reduction is confined only to the rural areas.

In terms of time spent on employment, employed men and women are estimated to spend 0.3 hours more on average due to the increase in employment. This implies (as we see in the assessment of the simulation in Appendix C) that the new jobs created are slightly above average in terms of weekly hours. The overall pattern holds for employed men and women in urban Mexico, where both spend 0.2 hours more per week on employment. But in rural areas, the increase for employed men is twice that of employed women, though still just 0.6 hours per week. The grey bar shows the change in household production hours induced by changes in employment, compared to the levels produced by the direct effects of the ECE expansion. Thus, the total change in household production time is the sum of the orange and grey columns. In all cases, the effect of increased employment on employed men and women is to increase their hours of household production, so that on balance, weekly hours are higher for employed men and women than before the policy intervention. The change in the total of employment and household production hours for employed women is an increase of 1.7 hours per week, while men see an increase of one hour per week combined.

Figure 15 Changes in Average Weekly Hours of Employment and Required Household Production of Employed Persons (18–74 years of age) by Sex, Actual and With Policy Intervention

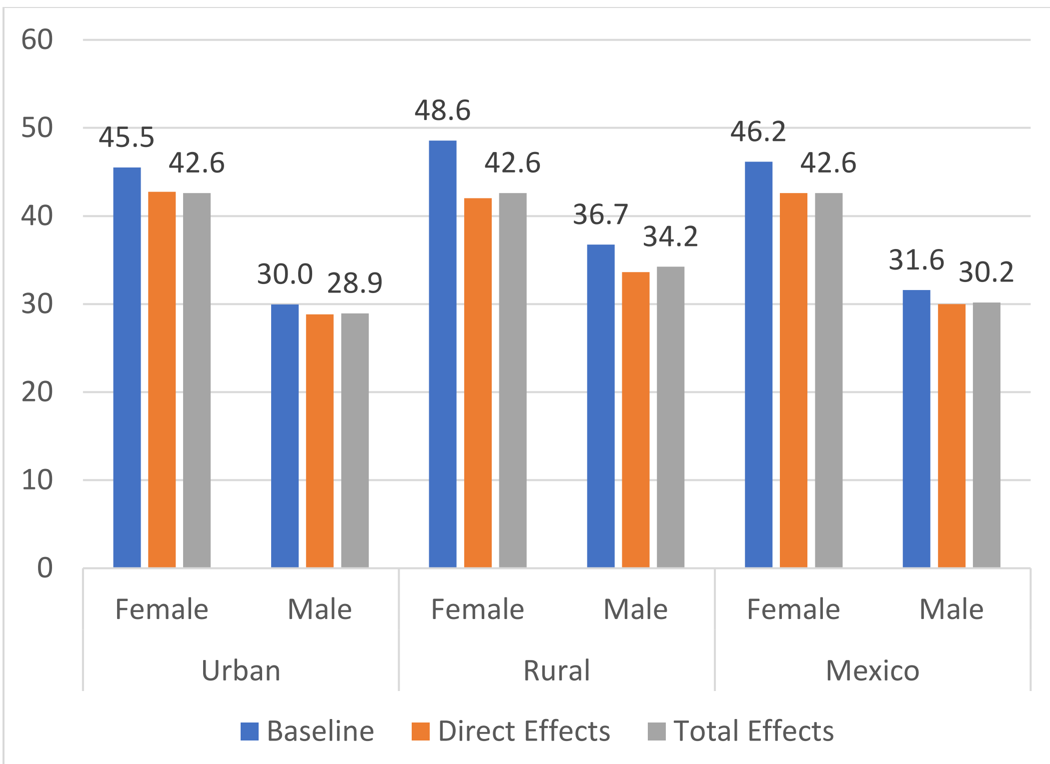


We now turn to the question of the changes in the patterns of time and income poverty as a result of the policy intervention. If job creation takes place predominantly among those that are, relative to the average employed person, more prone to fail in reconciling the demands of employment with household production requirements, the time poverty rate will face an upward pressure. On the other hand, expansion of childcare services, via lowering the household production requirements among families with young children, can exert a downward pressure on the time poverty rate. Redistribution of household production requirements as a result of the intervention has ambiguous potential effects. If it ends up lowering household production requirements for employed women without simultaneously raising the requirements for employed men that are already time-poor or may be pushed into time poverty, a win-win situation may emerge. However, there is no guarantee that redistribution can always reduce time poverty for all. Circumstances can differ across households to an extent that an a priori prediction may be hard to make (see Zacharias et al. 2021). The complex set of considerations with respect to time poverty makes the empirical examination of the policy intervention necessary to gauge its potential results.

We first scrutinize what happened to the rate of time poverty for employed men and women (Figure 16, below). In Mexico as a whole, the time poverty rate of employed men is predicted to fall by 1.6 percentage points (from 31.6 to 31 percent) as a direct result of the provision of childcare services. The decline is even greater for women (a 3.5 percentage point drop to 42.6 percent). These changes are slightly smaller in urban areas but almost doubled in rural areas. For example, the overall time poverty rate of employed women in rural areas is predicted to decline by 6.5 percentage points, to 42 percent.

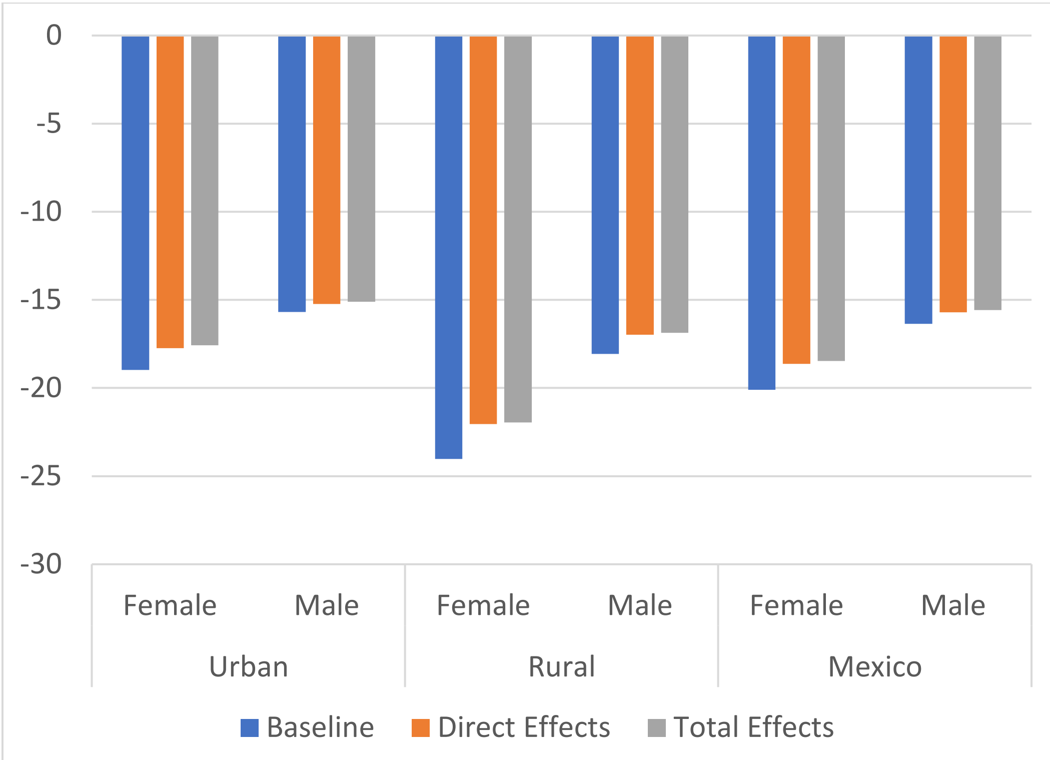
The impact of increased employment is to diminish the reductions in time poverty in Mexico as a whole by 0.2 percentage points for men, while employed women's time poverty rate remains the same. The time poverty rates for employed women and men in rural areas both increase relative to the direct effects by 0.6 percentage points. The changes for employed men and women in urban areas are small, but the time poverty rate for women falls by another 0.2 percentage points, while that of men rises by 0.2 percentage points. All employed men and women see time poverty rates decline in total, but in urban and rural Mexico as well as in Mexico overall, the decline is greater for women. Employed rural women saw the greatest decrease in their time poverty rate, at 5.9 percentage points. This brought them to a point of equality with their urban counterparts, but in all areas the time poverty rates of employed men are still significantly lower.

Figure 16 Time Poverty Rates of Employed Persons (18–74 years of age) by Sex and Location (percent), Actual and With Policy Intervention



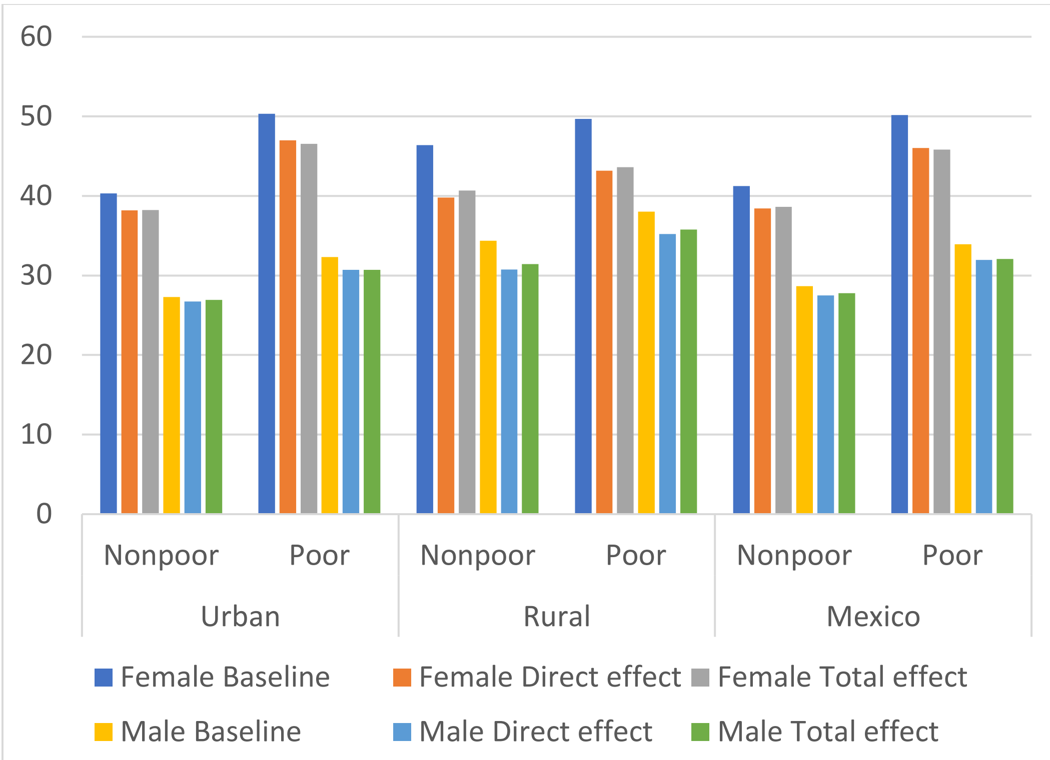
Next, we ask what will happen to the time deficits of the employed time-poor. As shown in Figure 17, below, both men and women experience a reduction in time deficits in our simulation both due to the direct effect of the policy and the indirect effect of job creation. The bulk of the decrease is produced by the direct effects of childcare services provision, which is estimated to reduce the average time deficits of time poor employed women by 1.5 hours per week. The reduction for women in rural areas is greater (2 hours per week), while in urban areas it is slightly smaller (1.2 hours per week). For time poor employed men, the reductions are smaller (0.7 hours per week overall, and 1.1 and 0.5 hours per week in rural and urban areas, respectively). The impact of the employment increase (and corresponding rearrangement of household production responsibilities in our simulation) is negligible for time poor employed women (just 0.2 hours overall and in urban Mexico and 0.1 hours in rural areas). For time poor men, the net effect was to reduce time deficits by 0.1 hours per week. Note that the reductions in time deficits along with the increase in average time spent on household production and paid work demonstrated above implies either that the reductions in time requirements are sufficient to make up for additional hours spent on income generation, that others in the household are taking a greater share of the responsibility for household production, or that both are happening.

Figure 17 Average Time Deficits of Time Poor Employed Persons (18-74 years of age) by Sex and Location (weekly hours), Actual and with Policy Intervention



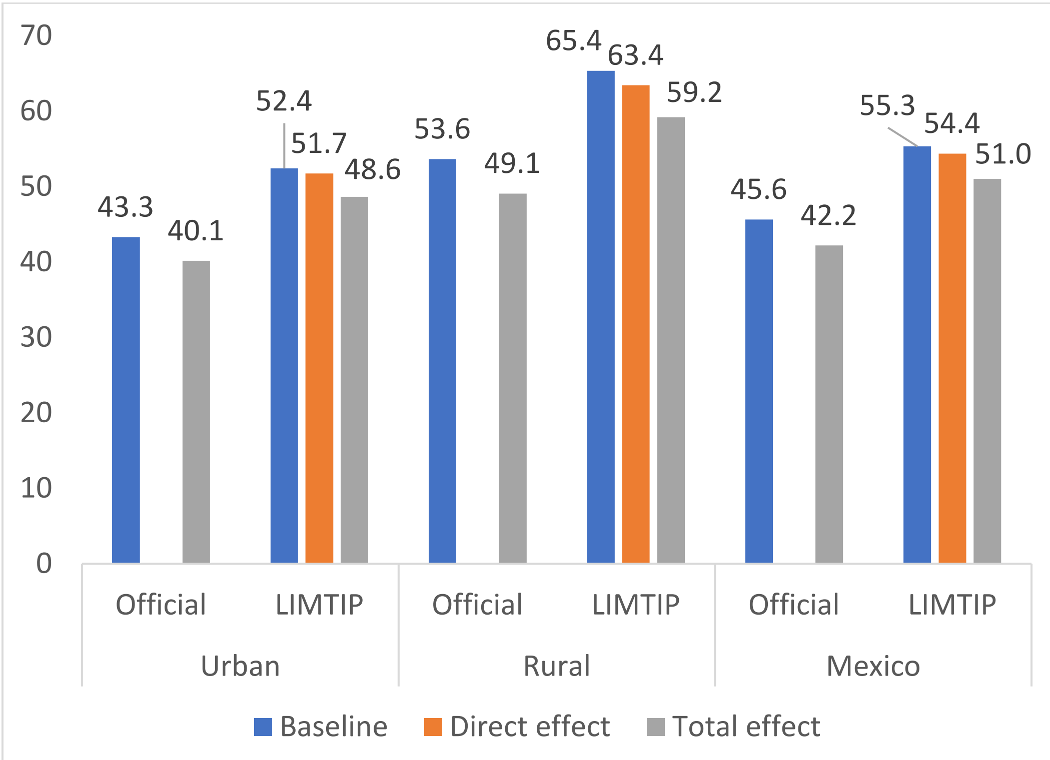
As we have seen before, the incidence of time poverty is higher among income-poor than income-nonpoor employed individuals. The policy intervention appears to reduce this gap, apart from among rural men (Figure 18, below). The direct effect of the ECE expansion is to reduce time poverty rates across the board. The reduction is higher for women and in rural areas. But the gap between poor and nonpoor employed women and men only declines in urban areas due to the direct effects of ECE expansion. Among rural women it rises by 0.1 percentage points, but for rural men it increases by 0.8 percentage points, to 3.4 and 4.4 percentage points, respectively. The employment effect slightly reverses the impact of the direct effects, except among urban men and women. The further decline among urban women (0.5 percentage points) is enough to reduce the overall rate of time poverty for poor employed women (by 0.2 percentage points) despite the increase among rural poor women (0.4 percentage points). The increase in the time poverty rate for employed men in rural areas is barely higher for those that are income poor compared to the nonpoor (0.7 versus 0.6 percentage points respectively), but the gap is larger among rural women (0.9 compared to 0.4 percentage points). For women in urban Mexico, estimated reductions in time poverty due directly to the expansion of ECE services is larger for the nonpoor than for the poor and the increase in time poverty due to the employment impacts are smaller for them as well. The combined result is a smaller reduction for nonpoor employed women in both urban (2.1 versus 3.8 percentage points for the poor) and rural (5.7 versus 6.1 percentage points) areas. The same pattern holds true for employed urban men, leading to a smaller reduction in time poverty rate for the nonpoor (0.4 percentage points) than the poor (1.6 percentage points). But for rural employed men, the opposite holds and nonpoor men's time poverty falls by 3 percentage points, compared to the 2.3 percentage drop for poor rural men.

Figure 18 Time Poverty Rates of Employed Persons (18–74 years of age) by Sex and Income Poverty Status (percent), Actual and With Policy Intervention



The increase in incomes resulting from the expansions in employment need not automatically produce a decline in income poverty if the time deficits generated by the job creation itself cannot be "bought off" with the additional earnings. However, we described above that the incidence of time poverty and average time deficit declined. Thus, the increase in earnings produces a reduction in income poverty among employed persons, both by the official and time-adjusted measure (see Figure 19, below). Official poverty falls by 3.4 percentage points in Mexico overall to 42.2 percent. The reduction is even larger in rural areas (4.5 percentage points). While we predicted that the direct effect of expanded ECE services provision would slightly reduce income poverty (by reducing time deficits), our simulation predicts that the employment expansion would have an even larger impact, reducing poverty overall by an additional 3.4 percentage points to 51 percent. Urban and rural poverty rates fell by an additional 3.1 and 4.2 percentage points, respectively, to 48.6 and 59.2 percent. In all three cases, the time-adjusted poverty rates are still higher than official poverty rate in the baseline. And hidden poverty is lower in the simulated total effects scenario than in the baseline (8.9 versus 9.7 percentage points in Mexico). Thus, we predict that although both official and time-adjusted income poverty would fall as a result of the policy intervention modeled here, official income poverty would fall less, precisely because it does not take into account the impact of the reduction in time poverty produced by the ECE expansion.

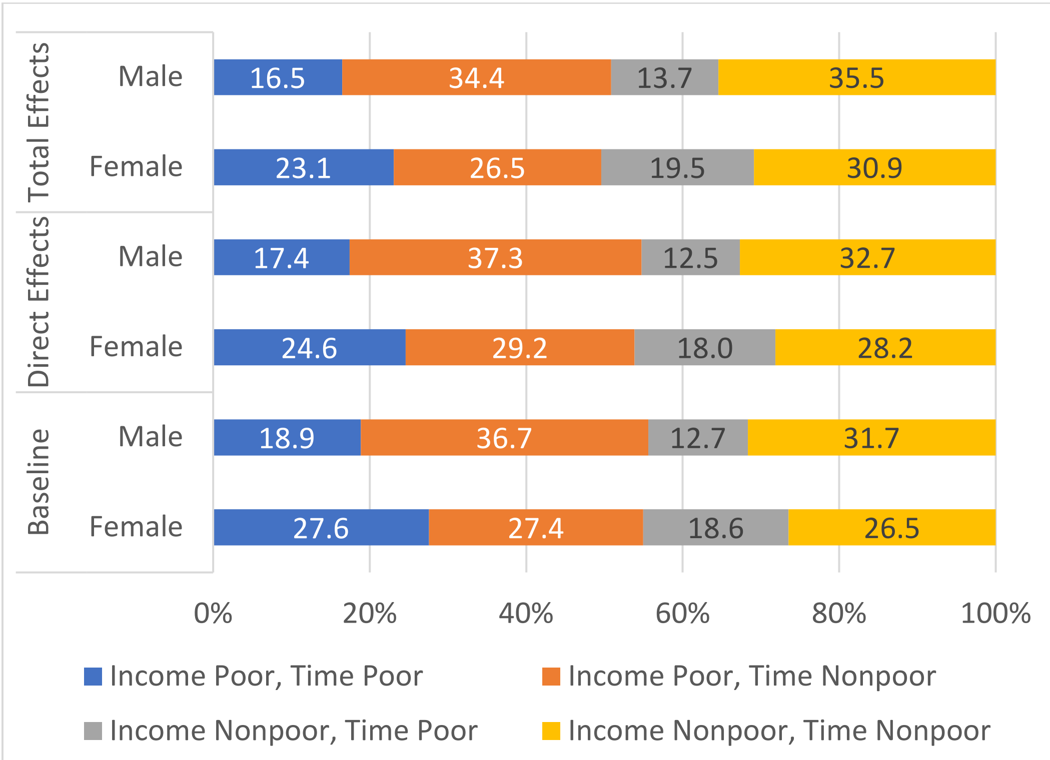
Figure 19 Official and Time-adjusted Poverty Rates of Employed Persons (18–74 years of age) by Area of Residence (percent), with and without Policy Intervention



The total simulated impact of the expansion of ECE services on the time and income poverty status of employed adults is presented in Figure 20, below. The share of all workers that face neither time nor income poverty has increased by 4 percentage points to 33.5 percent, with two thirds of the increase coming from the increased employment. There was also a decline in the share of all workers that were time poor and income poor (3.2 percentage points, mostly due to the direct effect on time use), there was a smaller reduction in the share that were income poor and time nonpoor (1.8 percentage points). The latter category grew as a direct effect of the ECE expansion, as many poor employed people shifted from time poor to time nonpoor. Although the overall estimated increase in the share of workers that were not income poor was similar for men and women (5.3 and 4.8 percent, respectively), that is where the similarity in experience ends.

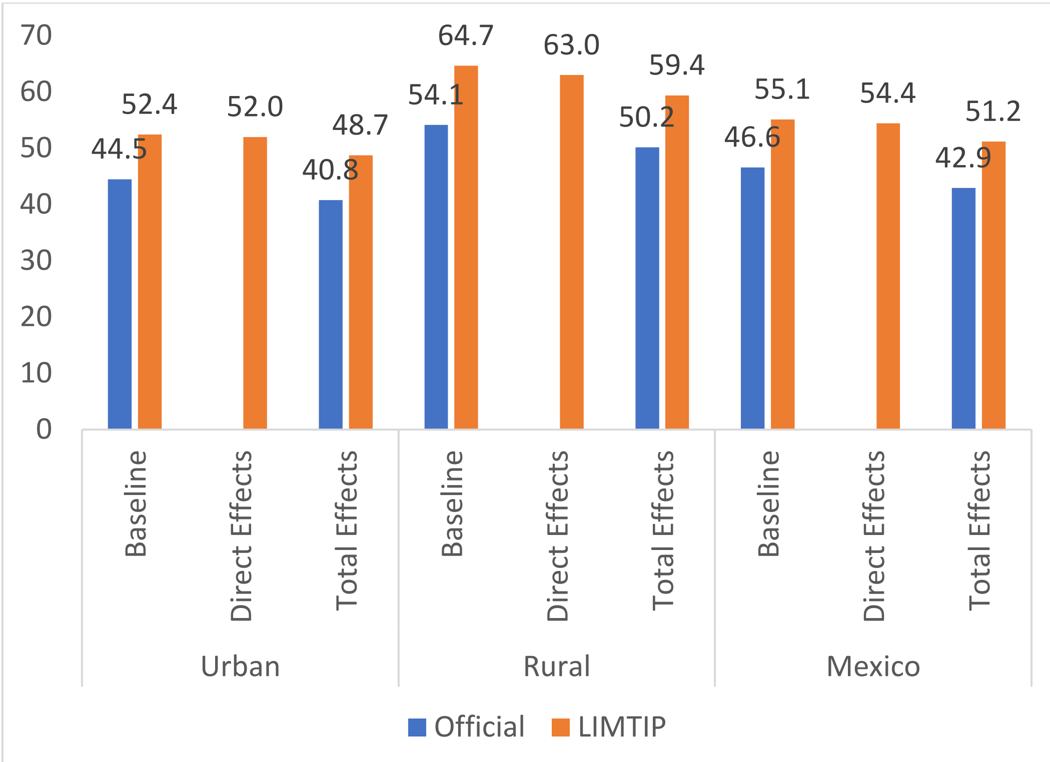
The reduction in the share of employed women that were both income and time poor was larger than that of men (4.5 versus 2.4 percentage points). For both men and women, the reduction in this category was mainly due to direct effects. Nonetheless, the share of employed women in the double bind of income and time poverty was still much greater than that of employed men (23.1 versus 16.5 percent). Employed women exiting income poverty were more likely than their male counterparts to have been time poor (4.5 of 5.3 percent, compared to 2.4 of 4.8 percent for men). Most of the reduction in income poverty comes from the employment increase in our simulation, and all of the reduction in overall time poverty among employed persons comes from the direct effect of ECE expansion. This is true for both employed men and women.

Figure 20 LIMTIP Distribution of Employed Persons (18–74 years of age) by Sex (percent), Actual and With Policy Intervention



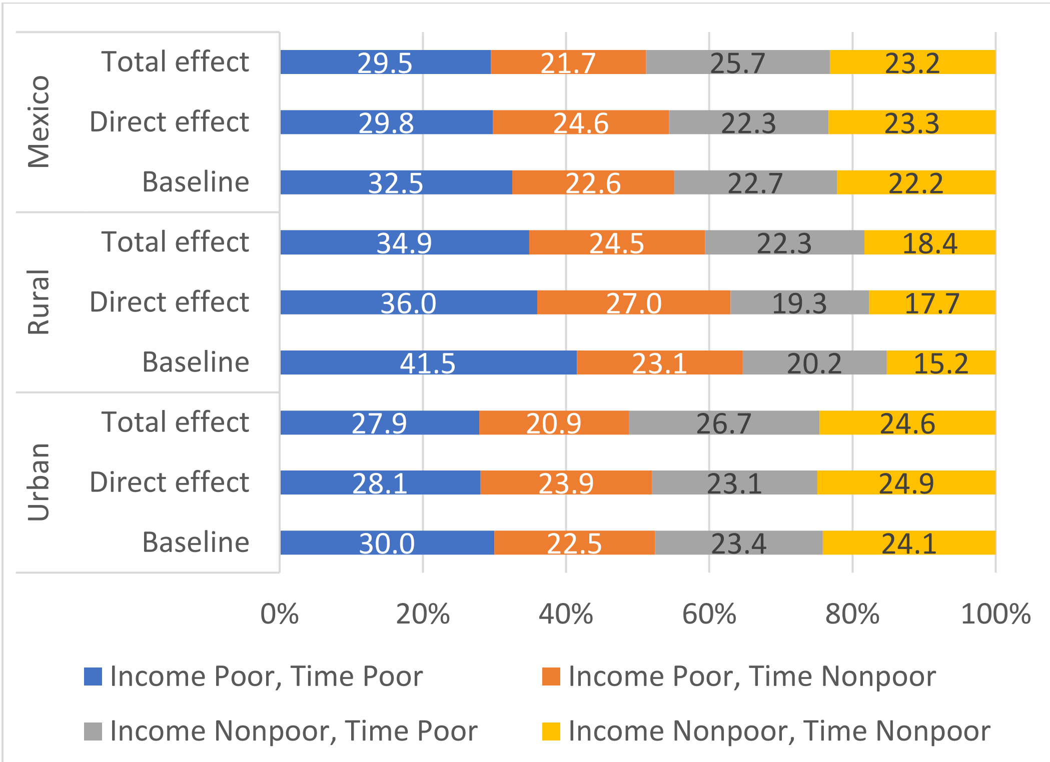
Turning to the impacts of the ECE expansion on employed households, we first examine the effects on income poverty (Figure 21 below). The overall effect of the policy intervention is to reduce income poverty (as measured by the LIMTIP) by 3.9 percentage points to 51.2 percent. In rural areas the decline was 5.3 percentage points to 59.4 percent but remained 7 percentage points higher than the baseline poverty rate for urban areas. In urban areas the reduction was 3.7 percentage points to 48.7 percent. Most of the overall reduction and that in the rural and urban areas is due to increased employment and the income that comes with it, rather than the reductions in time deficits from the direct effects of ECE expansion. The income effect of the employment increase outweighs the time-use effect even more at the household level than at the individual level. This is likely because household production responsibility is re-apportioned in the households that receive jobs in the employment simulation, as well as the fact that enrolling young children in childcare and preschool reduces the required hours of household production for everyone in the affected households.

Figure 21 Rate of Income Poverty among Employed Households by Location (percent), Actual and With Policy Intervention



Finally, we consider differences in the time and income poverty status of employed households as a result of the simulated ECE expansion. The changes due to the policy are more modest at the level of the household than at the individual level. Overall, there was just a 1.0 percentage point increase in the share of employed households that were both time nonpoor and income nonpoor (to 23.2 percent). This increase was entirely due to the direct impacts on time and income poverty of the ECE expansion. On the other end of the spectrum there was a 3 percentage point drop in the share of employed households that were both time and income poor. The overall impact of the expansion on time poverty rates for employed households was nil. However, there was a reduction of four percentage points in the income poverty rates for employed households. This result is due again to fact that the direct effects reduction of time poverty among the poor is exactly balanced by the increase in time poverty among the non-poor as a result of the increase in employment hours. The changes in urban poverty were roughly identical to the changes overall, but there was a slight increase (1.1 percentage points) in the share of employed households that were time poor. The changes in the rural areas were similar in direction to if larger in scale than the urban pattern. Among rural households, both the direct and indirect effects of the policy reduced the share that were both time and income poor (by 5.6 and 1.1 percentage points, respectively). Although the overall reduction in income poverty was the same as for urban areas, a smaller share traded income for time poverty in rural areas.

Figure 22 LIMTIP Distribution of Employed Households by Location (percent), Actual and With Policy Intervention



The significant reduction in income poverty we predict to come as a result of the policy is due in part to the reduction in thresholds for required household production that comes from the reduced responsibility for supervisory care of households with young children. This effect would tend to reduce time deficits and therefore hidden poverty. This reduction is reflected in line 3 of Table 11, below. It amounts to 285 thousand households leaving income poverty in Mexico, with over half of them in urban areas. This amounts to just 1.5 percent of poor households in Mexico. We would expect few if any households to be drawn into income poverty directly due to ECE expansion, though some may experience increased time poverty due to the time spent bringing children to childcare or preschool. And indeed, we find that to be the case (line 4): an increase of 0.3 percentage points in income poverty. The net direct impact of the ECE expansion is to reduce household income poverty in Mexico, by 1.2 percent. The reduction in urban areas is slightly lower (0.8 percent), while in rural areas the reduction is more pronounced (2.5 percent). The effects of the employment expansion are more nuanced. First and foremost, the increase in employment leads to an increase in incomes, which will reduce income poverty. However, some of the newly employed do encounter (increased) time deficits. The time demands of the job faced by the newly employed will be accompanied by a realignment of responsibilities for household production work among all members in households that receive jobs in the simulation. This might have the effect of reducing (or even eliminating) time deficits or *increasing* them, depending on the number of hours individual household members work for pay and how many adults in the household are not engaged in income-generating activities. Thus, there can be movement into or out of income poverty, if the increased income is not enough to make up for the increased time deficits induced by the increased employment in the household. The direction of movement for any particular household is an empirical question, as we discussed earlier. What we observe in our simulation is that, overall, the poverty-reducing impact of job creation overwhelmed its poverty-enhancing effect (lines 6 and 7 of Table 11).

Overall, we predict a reduction in the number of households in income poverty of more than one and a quarter million (6.7 percent). Of these, 297 thousand households are in the rural areas (4.8 percent of poor rural households) and 972 thousand households are in urban areas (5.5 percent of poor urban households). The number of households that fall into poverty as a result of the rise in employment is much smaller (62 thousand). These households experienced increases in time deficits that were larger in terms of replacement costs than the added income to the extent that the result was falling below the time-adjusted income poverty threshold. The total effects (lines 9 to 11) were large. The net reduction in households in income poverty was over 1.4 million, a 7.6 percent reduction in the incidence of poverty. Our prediction is that a greater share of rural poor households would be lifted out of poverty than urban households (8.5 versus 7.3 percent).

Table 11 Decomposition of the Change in the Number of Income-Poor Households (in thousands) Due to Policy Intervention

Line		**Number (in thousands)**			**Percentage of baseline**		
		Urban	Rural	Mexico	Urban	Rural	Mexico
1	Number in the baseline	14,132	4,708	18,840	100.0	100.0	100.0
2	Direct effects						
3	Reduction	-169	-116	-285	-1.2	-2.5	-1.5
4	Addition	63	1	64	0.4	0.0	0.3
5	Employment effects						
6	Reduction	-972	-297	-1,269	-6.9	-6.3	-6.7
7	Addition	50	12	62	0.4	0.3	0.3
8	Total effects						
9	Total reduction: Lines 3 + 6	-1,141	-413	-1,554	-8.1	-8.8	-8.2
10	Total addition: Line 4 + 7	113	13	126	0.8	0.3	0.7
11	Net reduction: Lines 9 + 10	-1,028	-400	-1,428	-7.3	-8.5	-7.6
12	Number after intervention: Lines 1 + 11	13,104	4,308	17,412	92.7	91.5	92.4

Notes: All households with at least one person between the ages of 18–74 are included in the calculations.
Line 3: Number of households that were nonpoor after accounting for direct effects but were poor in the baseline.
Line 4: Number of households that were poor after accounting for direct effects but were nonpoor in the baseline.
Line 6: Number of households that were nonpoor after accounting for employment effects but were poor after accounting for direct effects.
Line 7: Number of households that were poor after accounting for employment effects but were nonpoor after accounting for direct effects.

8. Conclusions

Our estimates indicate that the expansion of ECE services in Mexico to the target levels of enrollment for young children will reduce both time and income poverty for individuals and households. The direct impacts are predicted to be somewhat smaller in scale than the indirect impacts due to the increase in employment. The former has a larger impact on time poverty and the latter, on income poverty. In each case there are important differences in outcomes by gender and by area of residence.

To begin with, we produced a new set of estimates of the LIMTIP for Mexico for 2020. The LIMTIP poverty rate of employed households in Mexico in 2020 is 55.1 percent, compared to the official poverty rate of 46.6 percent. Thus, hidden poverty affects 8.5 percent of employed households.

The mixed direct impact of expanded early childhood education provision in Mexico (as in other countries) sheds light on the fact that ECE services may have more impact on the time spent on household production work for women than for men, who seem to do more household production work in households with enrolled young children. Access to ECE services may increase the flexibility women have to engage in both unpaid and paid income-generating activities during the times of the day that childcare is being provided. Especially for poorer women, this added flexibility may mean greater engagement with the labor force. But that engagement comes at a cost of *higher* time deficits overall for women if there is inadequate reduction in their share of the responsibility for household production: the time poverty rate of women job recipients that live in households with young children nearly tripled compared to the pre-existing conditions.

The impact of employment changes as a result of the policy interventions is much larger in terms of income poverty, though it also has the effect of undermining the gains made by some households in terms of time poverty. The additional employment is estimated to reduce official income poverty by more than the drop in the time-adjusted poverty rate. Nevertheless, we estimate that the overall impact of the policy intervention is to reduce income poverty by more than 4.3 percentage points for employed individuals and 3.9 percentage points for employed households.

Our results indicate that caution should be used in promoting the benefits of ECE provision for women's economic empowerment. It is certainly the case that there will be some reduction in time deficits for women as a direct impact of the expanded ECE services. However, time spent on other aspects of household production (doing the laundry, for example) will not be greatly affected and if women retain the greater share of responsibility for these other activities, their time poverty may not be reduced, especially if they take advantage of the flexibility afforded them by the provision of ECE services to engage in the labor force. Indeed, women are the main beneficiaries of the newly created employment in ECE services, but employed women still do a much greater share of household production work. Employed women spend an average of 7 to 8 hours more on household and income-generating work combined than employed men do and have much higher rates of time poverty as a result. If an increase in welfare is the goal, we predict that the policy is a qualified success. In order for the full potential welfare-enhancing impacts of ECE expansion is to be realized, additional complementary measures that would reduce the gender disparity in household production, through redistribution of tasks among couples for example, needs to be considered as well.

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Appendices

A. Statistical Matching of ENIGH 2020 with ENUT 2019

This appendix describes the construction of synthetic dataset created for use in estimation of the Levy Institute Measure of Time and Income Poverty (LIMTIP) for Mexico in 2020. Construction of LIMTIP estimates requires a variety of information for households. In addition to basic demographics, the estimation process requires information about income and time use. No single data set has all the required data for Mexico. Thus, to produce LIMTIP estimates, a synthetic data file is created by combining two source data sets with statistical matching.[8] We use the *Encuesta Nacional de Ingresos y Gastos de los Hogares* (ENIGH) for 2020 as the base data set, matching it with the *Encuesta Nacional sobre Uso del Tiempo* (ENUT) for 2019, which includes rich time use data. Each of these data sets covers the entire country. This appendix is organized as follows. The source datasets are described and their demographic characteristics are compared. Then the quality of the match is reviewed.

Data and Alignment

The source data sets for the time use match for the LIMTIP estimates for Mexico are the 2020 ENIGH and the 2019 ENUT. We use individual records from the 2020 ENIGH file, excluding those living in group quarters or in the Armed Forces. This results 315,619 individual records, representing 126,760,860 individuals in Mexico. Since the time use data in the ENUT covers individuals aged 12 years of age and older, we discard younger individuals from the ENIGH file. This leaves 254,223 records, which represents 103,214,850 individuals when weighted. The ENUT file, from a nationally representative sample survey, contains records for all individuals, but time use data only for those twelve years of age and older. The entire data set contains 93,485 individual records, representing 126,371,728 individuals. Once those individuals aged 11 or less are dropped, 71,404 records remain, representing 101,145,172 individuals.

The strata variables for this match are the number of children and adults in the household, an indicator for the presence of a non-employed, non-disabled adult in the household, an indicator for the household being within 75 and 150 percent of the poverty line (these two identify the reference group for the estimation of thresholds for household production time), a geographical indicator for rural households, the household income category, the sex of the individual and an indicator for employment of the individual. The geographical indicator is never dropped in the matching process, so all matches are within rural and urban segments of the recipient and donor data sets.[9] Table A1 compares the distribution of individuals by these variables in the two data sets. Since both surveys are nationally representative and carried out within one year of each other, we can expect them to be well aligned. The distribution of individuals by number of children in household is within one percentage point in the two surveys across number of children. There are 2.0 and 3.3% fewer individuals in household with one and two adults, respectively, in the ENUT than in the ENIGH, and so, more individuals in households with three or more adults in the latter. About 1.9% more individuals are in households with at least one non-employed adult in the time use survey, than in the income survey, while the difference in the number of individuals in households within the poverty band in the two surveys is 2.2%. The distribution by household income is less close between the two surveys, with households in the ENIGH 6% more likely to be in the lowest income category. The distribution of individuals by sex is very close in the two

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[8] See Kum and Masterson (2010) for details of the statistical matching procedure that we use.

[9] Rural is defined in the Mexican national poverty statistics as in a municipality with fewer than 2,500 residents.

surveys, with females only slightly less common (0.5%) in the ENIGH than in the ENUT. There are 2.2% fewer employed individuals and 0.2% fewer inactive individuals in the ENIGH than in the ENUT. Finally, there is no significant difference in the distribution of individuals by rural/urban status. So, as expected, we have a very close alignment between the two surveys along almost all eight strata variables.

Table A1 Alignment of Strata Variables, Mexico

	ENIGH 2020	ENUT 2019	Diff
Number of children in household			
0	36.84%	36.09%	-0.75%
1	24.27%	24.13%	-0.14%
2	21.94%	22.55%	0.61%
3	11.19%	10.98%	-0.21%
4+	5.76%	6.25%	0.49%
Number of adults in the HH			
0	0.02%	0.02%	0.00%
1	6.80%	8.78%	1.98%
2	36.30%	39.58%	3.28%
3	25.68%	24.60%	-1.08%
4	17.82%	16.23%	-1.59%
5	8.34%	6.34%	-2.00%
6	3.16%	2.74%	-0.42%
7+	1.88%	1.70%	-0.18%
Presence of nonemployed, non-disabled adult in HH			
No	33.06%	34.98%	1.92%
Yes	66.94%	65.02%	-1.92%
Indicator that HH is between 75% and 150% of the poverty line			
No	62.90%	65.14%	2.24%
Yes	37.10%	34.86%	-2.24%
Rural Household			
No	77.94%	77.91%	-0.03%
Yes	22.06%	22.09%	0.03%
Household Income Category			
Less than 2500	35.19%	29.02%	-6.17%
2500 to 4999	35.93%	33.82%	-2.11%
5000 to 7499	14.52%	18.92%	4.40%
7500 to 14999	10.80%	13.88%	3.08%
15000 or more	3.55%	4.36%	0.81%
Sex of individual			
Female	52.15%	52.65%	0.50%
Male	47.85%	47.35%	-0.50%
Labor force status of individual			
Employed	56.29%	58.52%	2.23%
Unemployed	3.12%	0.66%	-2.46%
Inactive	40.59%	40.82%	0.23%

Match Quality

Turning to the results of the match, we first look to the distribution of matched records by matching round in Table A2. The bulk of the matches, 73.8 percent, occur in the first round, in which all of the recipients are matched with donor records that have identical values for all eight strata variables. the remainder of the records required an additional 19 rounds of matching to completely exhaust individual records. Just 1.4 percent of records received no match at all.[10]

Table A2 Distribution of Recipient Observations by Matching Round

Round	Number	Percentage	Cumulative Percentage
1	187,648	73.8%	73.8%
2	6,578	2.6%	76.4%
3	1,360	0.5%	76.9%
4	22,566	8.9%	85.8%
5	80	0.0%	85.8%
6	1,546	0.6%	86.5%
7	139	0.1%	86.5%
8	14,145	5.6%	92.1%
9	3,826	1.5%	93.6%
10	1,037	0.4%	94.0%
11	1,727	0.7%	94.7%
12	277	0.1%	94.8%
13	798	0.3%	95.1%
14	2,047	0.8%	95.9%
15	835	0.3%	96.2%
16	3,919	1.5%	97.8%
17	218	0.1%	97.8%
18	289	0.1%	98.0%
19	1,359	0.5%	98.5%
20	230	0.1%	98.6%
21	3,599	1.4%	100.0%
Total	254,223		

Table A3 provides a comparison of the distribution of weekly hours of household production in urban and rural areas in the ENUT and the matched file. The percentile ratios are all relatively close, with the ratios for urban areas being slightly higher, and those for rural areas slightly lower in each case. The Gini coefficients are also virtually identical.

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[10] Round 21 represents recipient observations that remained unmatched after all of the donor records had been used in matches. The unmatched records are assigned the median values of hours of household production for their original matching cells.

Table A3 Distribution of Household Production in 2019 ENUT and Matched File

		p90/p10	p90/p50	p50/p10	p75/p25	p75/p50	p50/p25	Gini
ENUT09	Urban	14.184	2.797	5.071	4.244	1.892	2.243	0.441
	Rural	16.682	2.731	6.108	4.781	1.968	2.429	0.442
Match	Urban	13.967	2.821	4.951	4.232	1.921	2.203	0.441
	Rural	16.346	2.763	5.916	4.732	1.985	2.384	0.442
Ratio	Urban	98.5%	100.9%	97.6%	99.7%	101.5%	98.2%	100.1%
	Rural	98.0%	101.2%	96.9%	99.0%	100.9%	98.1%	100.1%

Table A4 breaks down the mean and median of the three categories of household production and the total in the matched file and the ENUT.[11] We can see that for all four variables the difference in the matched and the source file's mean and medians are small, with the largest differences in median rural care and total weekly hours of just over 1.5% (about 15 and 20 minutes, respectively) higher in the matched file than in the ENUT.

Table A4 Comparison of Mean and Median Time Use Variables in 2019 ENUT and Matched File

		Mean				Median			
		HH Production	Core	Care	Procure-ment	HH Production	Core	Care	Procure-ment
ENUT19	Urban	24.1	18.6	3.9	1.7	18.7	13.9	0.0	1.0
	Rural	28.3	22.3	4.5	1.5	22.2	16.7	0.4	0.5
MATCH	Urban	24.1	18.6	3.8	1.6	18.5	13.8	0.0	1.0
	Rural	28.0	22.1	4.4	1.4	21.7	16.3	0.4	0.5
Ratio	Urban	99.7%	99.9%	98.2%	98.8%	99.0%	99.1%		98.1%
	Rural	98.9%	98.8%	98.4%	98.6%	97.6%	97.5%	105.3%	100.0%

Examination of the quality of the match within population sub-groups shows generally good results. Figure A1 displays ratios of mean weekly hours of household production between the matched file and the ENUT for the seven strata variables in rural and urban areas. In most cases, the average weekly hours in the matched file are within 3% of the ENUT average. The worst case is that of the rural employed, who have 11% higher weekly average hours in the matched file than in the ENUT. This represents a difference of 2.3 hours per week between the ENUT and the matched file.

[11] The three categories are care (child care, elder care, etc.), procurement (shopping, etc.), and core (cooking, cleaning, laundry, etc.).

Figure A1 Ratio of Mean HH Production Weekly Hours by Category (Match/ENUT 2019)

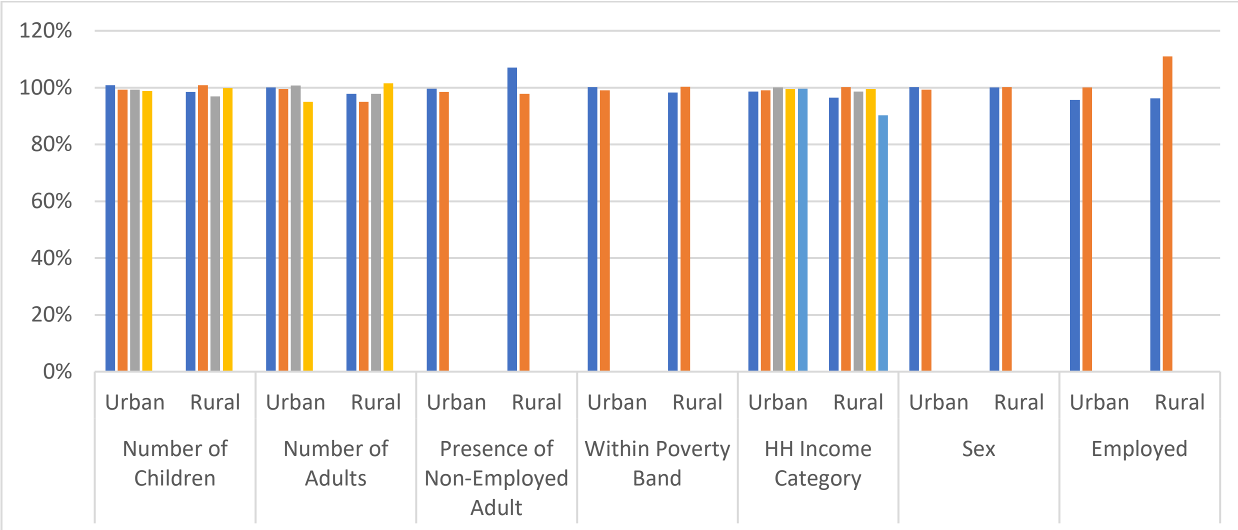


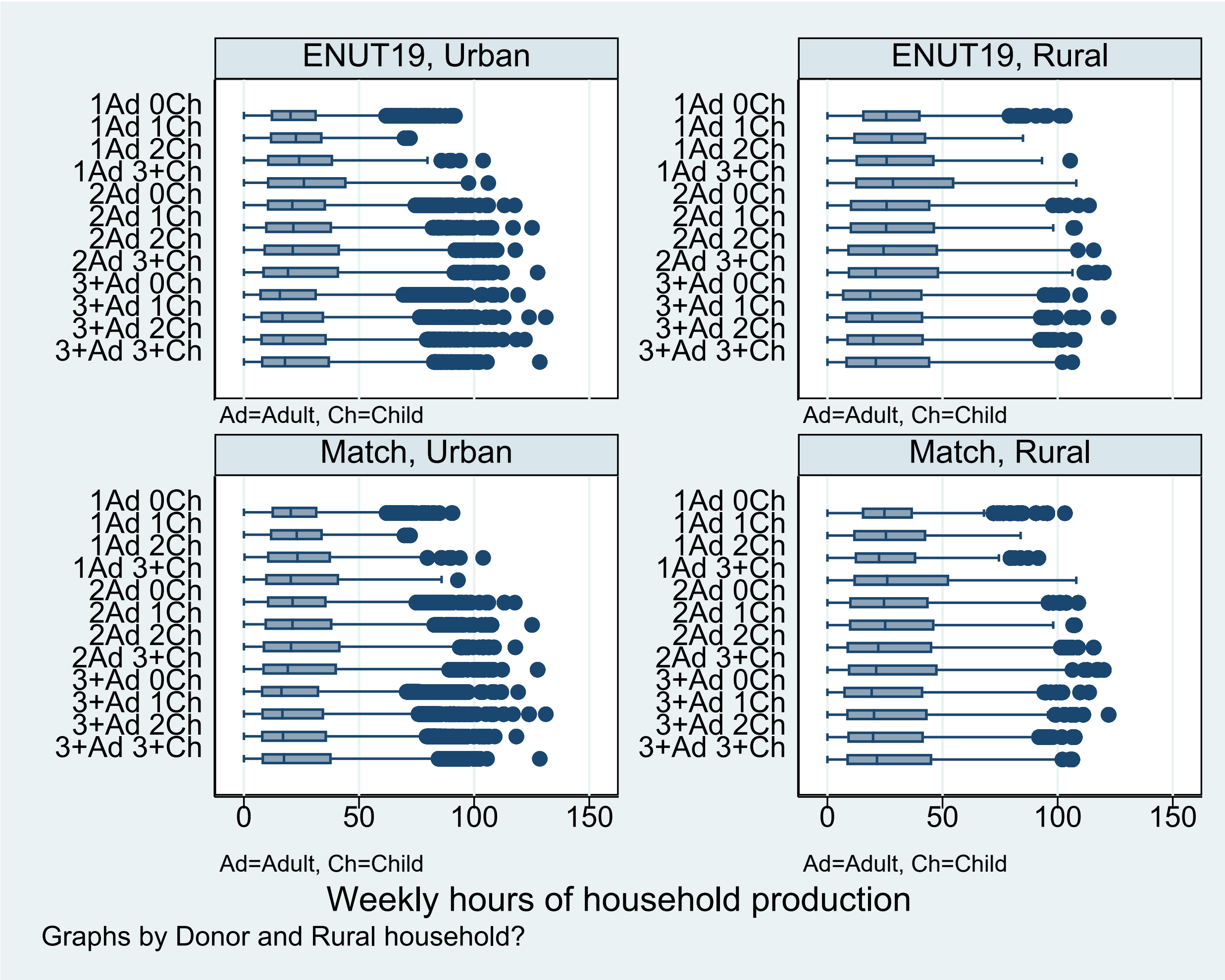
Table A5 has the actual numbers, and we can see that even the larger percentage differences represent relatively small differences in hours per week. The rural employed have 2.3 hours more household production per week in the matched file and individuals in rural households with the highest income have 2.7 hours less in the matched file, the largest deviation by averages. Notice that the ratios by category are well reproduced in the matched file, even for the categories with the largest average deviation. The largest difference is by sex in rural areas, as we would expect given the differences in the averages for rural females. The medians closely follow the patterns of the averages with similar differences in the rural areas by employment and income category.

Table A5 Mean Weekly Hours of Household Production, 2019 ENUT and Matched File

	Mean values of HH Production					
Urban	ENUT09	Match	Ratio			
HH Production	24.1	24.1	99.7%			
Core	18.6	18.6	99.9%			
Care	3.9	3.8	98.2%			
Procurement	1.7	1.6	98.8%			
Personal	72.9	73.0	100.1%			
Share (transf.)	0.380	0.380	100.0%			
Share (calc.)	0.380	0.350	92.1%			
Rural						
HH Production	28.3	28.0	98.9%			
Core	22.3	22.1	98.8%			
Care	4.5	4.4	98.4%			
Procurement	1.5	1.4	98.6%			
Personal	77.0	76.8	99.7%			
Share (transf.)	0.370	0.360	97.3%			
Share (calc.)	0.370	0.340	91.9%			
Distribution among population subgroups				Ratio of Mean Values		
					ENUT09	Match
Number of Children						
Urban				Urban		
0	22.77	22.96	100.8%	*0/3+*	0.78	0.79
1	24.12	23.95	99.3%	*1/3+*	0.83	0.82
2	25.36	25.17	99.3%	*2/3+*	0.87	0.87
3+	25.77	25.47	98.8%			
Rural				Rural		
0	27.53	27.11	98.5%	*0/3+*	0.95	0.93
1	27.91	28.15	100.9%	*1/3+*	0.96	0.97
2	28.56	27.69	97.0%	*2/3+*	0.98	0.95
3+	29.08	29.04	99.9%			
Number of Adults						
Urban				Urban		
1	24.40	24.41	100.0%	*2/1*	0.85	0.89
2	25.77	25.65	99.5%	*3+/1*	0.76	0.80
3+	22.86	23.03	100.7%			
Rural				Rural		
1	30.25	28.74	95.0%	*2/1*	0.98	1.01
2	29.64	29.00	97.8%	*3+/1*	0.88	0.94
3+	26.68	27.10	101.6%			
Presence of Non-Employed Adult?						
Urban				Urban		
No	21.83	21.75	99.6%	*Yes/No*	1.17	1.15
Yes	25.49	25.10	98.5%			
Rural				Rural		
No	24.88	26.64	107.1%	*Yes/No*	1.18	1.08
Yes	29.47	28.81	97.8%			
Within Poverty Band?						
Urban				Urban		
No	24.10	24.13	100.1%	*Yes/No*	1.00	0.99
Yes	24.15	23.91	99.0%			
Rural				Rural		
No	28.73	28.24	98.3%	*Yes/No*	0.95	0.97
Yes	27.38	27.47	100.3%			
Household Income					Over All	
Urban				Urban		
Less than 2500	25.31	24.96	98.6%	*Less than 2500*	0.90	0.89
2500 to 4999	24.15	23.93	99.1%	*2500 to 4999*	0.85	0.86
5000 to 7499	23.62	23.63	100.0%	*5000 to 7499*	0.84	0.85
7500 to 14999	23.13	23.02	99.5%	*7500 to 14999*	0.82	0.82
15000 or more	23.57	23.47	99.6%	*15000 or more*	0.83	0.84
Rural				Rural		
Less than 2500	30.16	29.08	96.4%	*Less than 2500*	1.07	1.04
2500 to 4999	26.89	26.94	100.2%	*2500 to 4999*	0.95	0.96
5000 to 7499	26.15	25.77	98.5%	*5000 to 7499*	0.93	0.92
7500 to 14999	25.34	25.21	99.5%	*7500 to 14999*	0.90	0.90
15000 or more	28.22	25.46	90.2%	*15000 or more*	1.00	0.91
Employed?						
Urban				Urban		
No	30.43	29.12	95.7%	*Yes/No*	0.66	0.69
Yes	19.95	19.96	100.1%			
Rural				Rural		
No	36.37	34.98	96.2%	*Yes/No*	0.58	0.66
Yes	20.93	23.24	111.0%			
Sex						
Urban				Urban		
Female	33.65	33.72	100.2%	*Female/Male*	2.49	2.51
Male	13.52	13.42	99.3%			
Rural				Rural		
Female	40.96	40.98	100.0%	*Female/Male*	2.90	2.89
Male	14.13	14.16	100.2%			

The extent to which the matched file reproduces the distribution of total weekly hours of household production in households in the reference group is demonstrated in Figure A2. We can see there are some differences between the matched file and the ENUT. The upper tails are fatter for each of the cells in the reference groups.

Figure A2 Household Production by Matching Cells, ENUT 2019 and Matched File



The ratios of the average and median household total weekly hours of production for the reference group in the matched file to the ENUT are presented in Table A6. In both rural and urban areas, the largest differences are in one-adult households with children. These are the cells in the reference group which are the smallest, meaning they are likeliest to be off substantially, but also make less difference in terms of the target measure. Other cells have somewhat large differences, but most of these are households with three or more adults, which, again, are smaller cells. The largest difference among two-adult households is the average weekly hours for rural households with two adults and two children, among which households have 12% higher weekly hours of household production in the matched file than in the ENUT. Overall, the distribution of household production is well preserved in the matching process, even at this level of detail.

Table A6 Household Production Weekly Hours for Households in Reference Group, Ratio of Matched File to 2019 ENUT

			Number of Children			
	Number of Adults		0	1	2	3+
Urban	1	Mean	100.8%	105.4%	81.3%	166.3%
		Median	100.3%	101.7%	105.6%	136.6%
	2	Mean	97.7%	97.2%	105.9%	104.1%
		Median	98.1%	97.8%	102.6%	97.2%
	3+	Mean	107.9%	104.0%	101.7%	102.5%
		Median	107.0%	107.6%	100.9%	104.7%
Rural	1	Mean	103.9%	88.6%	86.2%	120.9%
		Median	107.9%	95.0%	74.7%	122.4%
	2	Mean	103.5%	100.6%	108.4%	105.7%
		Median	106.1%	100.3%	102.8%	105.7%
	3+	Mean	110.3%	102.4%	107.4%	97.2%
		Median	119.9%	106.3%	112.7%	96.9%

In sum, the quality of the match is very good, though there are discrepancies for some small subgroups. The overall distribution is transferred with very good accuracy. And the distributions within most sub-groups, such as one adult with two children, is transferred with good precision.

B. Estimation of Direct Effects of Childcare Expansion on Time Use

We examined the direct impact of our proposed policy interventions on how time individuals devote to household production activities in chapter 6. The purpose of this appendix is to present the econometric models used in deriving the estimates described in chapter 6.

Data

We obtained the elasticities of time allocation with respect to the increased availability of childcare from models estimated based on the ENUT 2019. We use the enrollment of children in four age groups (0–2 years of age, 3 years of age, 4 years of age, and 5 years of age) in a preschool (*pre-escolar*) or childcare (*guarderia*). These are identified for each child in surveyed households. The proposed intervention is to increase the enrollment rate to 66 percent for 0 to 2 year-olds, 80 percent for 3 year-olds, and 100 percent for 4 and 5 year-olds.

Models

The goal of the estimation is to ascertain the impact of expanding ECE on time spent on household production. We define a subsample of the sample collected in the time use survey as the group of persons that have the potential to be directly affected ("beneficiaries") in terms of their time use. These are all households with at least one child aged less than six years old.

To identify the impact of the policy interventions on individuals' time use decisions, we use a Tobit model under the assumption that the number of hours people engage on a specific activity is censored at zero (see, for example, Woolridge [2012, 525]). This model also assumes that the same process that determines the decisions to engage in a specific activity also determines the number of hours dedicated to that activity. This relationship can be written as follows:

$$t_j^* = x\beta + \delta z + u$$

$$t_j = \max(0, t_j^*)$$

In the equations above, t_j^* is the latent number of hours a person would like to spend on activity j, t_j is the observed number of hours that a person is currently engaged in activity j, x is a set of controls variables, z is a variable capturing the policy intervention, and u is normally distribution error with mean zero and standard deviation σ, with all controls assumed to be uncorrelated to this error.

To ascertain the impact of the expansion of ECE on time spent on household production, we ran separate models for girls, boys, women, and men, in rural and urban areas. In order to obtain reasonable and consistent estimates for the effect of the policy interventions on time use allocations, we select a minimum set of controls to estimate the effect of the policy intervention that is as close to a causal effect as possible. In addition to the standard age and education characteristics, we also include controls for job characteristics, marital status, household size and household composition, household income, ownership of appliances, and access to public utilities (water, sewer, electricity).

Additionally, for children younger than 4 years old, we estimate the likelihood of a household's children being enrolled in two separate regressions, one for children of 3 years of age and another for children 0-2 years of age. We use a probit regression with a similar set of household-level characteristics. The results are presented in Table B3, below. We predict the likelihood based on the results and use the prediction to assign enrollment into the new ECE spots in order to reach the policy target.

Results

The results of the Tobit regressions are presented in Tables B1 and B2. Paying attention to the policy intervention variables, we observe that the results are consistent with the expectations of the direction of the impact of the proposed policy implementations, at least for women. For women in urban areas the largest estimated reduction (approximately one hour and twenty minutes) comes from the enrollment of three year olds. The enrollment of infants is estimated to reduce urban women's hours of household production time by a half an hour hour and the enrollment of four- and five-year-olds by 45 minutes and a half an hour per week, respectively. For rural women, reductions are similarly modest: two hours for enrollment of children aged 0 to 2 and one and a quarter hour for children aged 4. Because most of the time spent caring for children is in supervisory care, frequently as a secondary activity, we expect to see only modest reductions.

To estimate the impacts of enrolling children in preschool or childcare, we predict household production time with each of the policy variables in turn set to zero, then predict again with them each set to one. We calculate the percentage change for each of the four policy groups and for boys, girls, women, and men.[12] For households with children aged 4 and 5 that were not previously enrolled in preschool, we multiply the average percentage changes for those two policy groups for each individual by their observed hours of household production. We do the same for households with children aged 0 to 3, but since not all children under 4 will be enrolled, we must first select which of these households will be beneficiary households.

We use a probit estimation of the likelihood of households enrolling children aged 0 to 2 and aged 3, separately. We use the result to predict the likelihood of enrolling children in each group for each household with children in those groups. In the simulation, selection into the treatment group is by household (so all children in the policy groups, aged 0 to 2 and age 3, in a recipient household will be enrolled). To select the beneficiaries for each of the two policies, we sort the households in descending order, first by actual enrollment status, then by their predicted likelihood of enrolling the children in their household. We then calculate the weighted cumulative distribution function for the predicted likelihood for all of the households with children in the policy age group. Finally, we assign enrollment to all households below the threshold share for each policy group (66 and 80 percent for ages 0 to 2 and 3, respectively).

[12] The cutoff age between girls and women and between boys and men is 18 years of age: 18 years and up are adults, and so, men and women.

Table B1 Results of Tobit Regressions of Household Production Weekly Hours by Age and Sex for Urban Areas

	Boys	Men	Girls	Women
Children aged 0 to 2 enrolled	5.116*	-2.458*	0.606	-0.544
	(2.50)	(1.12)	(2.90)	(0.98)
Children aged 3 enrolled	1.339	-0.669	-3.701	-1.304
	(1.80)	(1.14)	(2.04)	(0.92)
Number of children aged 4 enrolled in household	-0.030	-0.601	-9.051***	-0.850
	(1.99)	(1.18)	(2.59)	(1.11)
Number of children aged 5 enrolled in household	-1.143	-0.337	-8.009**	-1.593
	(1.99)	(1.21)	(2.61)	(1.12)
Number of children aged 0 to 2 in household	0.768	1.184*	5.095***	4.135***
	(0.90)	(0.54)	(1.17)	(0.47)
Number of children aged 3 in household	0.869	0.212	2.551	1.771**
	(1.24)	(0.77)	(1.68)	(0.67)
Number of children aged 4 to 5 in household	1.803	0.007	8.757***	2.176*
	(1.93)	(1.12)	(2.49)	(1.06)
Number of Adults	-0.269		-1.783***	
	(0.32)		(0.35)	
Married	-0.499	4.669***	21.181***	11.630***
	(2.64)	(0.62)	(1.97)	(0.58)
Can you read and write?	3.864	3.894*	1.665	6.090***
	(4.94)	(1.76)	(5.00)	(1.27)
Primary	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Secondary	-0.659	0.376	-3.037*	4.216***
	(1.18)	(0.81)	(1.38)	(0.67)
High school	-4.270	2.219*	-0.863	4.068***
	(4.75)	(0.94)	(4.15)	(0.79)
Undergraduate studies	-13.602	5.460***		4.516***
	(9.83)	(1.07)		(0.88)
Age	0.547	-0.059*	3.071***	-0.031
	(0.34)	(0.03)	(0.43)	(0.02)
Employed	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Unemployed	6.565	9.388**	0.377	2.811
	(6.37)	(3.12)	(21.38)	(3.73)
Not in Labor Force	-8.898***	7.776***	0.308	10.405***
	(2.58)	(1.65)	(3.27)	(1.15)
Married Couple with Children	0.000	0.000	0.000	0.000

	(.)	(.)	(.)	(.)
Female Head	-0.015	0.552	-2.089	-2.111**
	(0.91)	(0.71)	(1.17)	(0.75)
Male Head	-0.576	3.008*	0.254	-1.284
	(2.22)	(1.22)	(2.72)	(1.46)
Total current income per capita (income poverty)	-0.000	0.000**	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Stove	3.681	2.332	-3.742	2.822*
	(2.42)	(1.51)	(2.47)	(1.29)
Laundry	-0.261	0.610	-3.555**	-0.280
	(1.01)	(0.69)	(1.23)	(0.58)
Microwave oven	0.486	0.969	-1.781	1.046*
	(0.90)	(0.59)	(1.21)	(0.51)
iron	0.202	-0.053	-0.538	0.832
	(1.29)	(0.84)	(1.33)	(0.71)
Blender	2.402	-1.632	0.381	0.366
	(1.87)	(1.30)	(1.87)	(1.03)
gas	-1.706	0.418	-3.836	4.186***
	(1.97)	(1.24)	(2.19)	(1.15)
Sink	2.038*	-0.660	-2.357*	1.015
	(0.88)	(0.64)	(1.11)	(0.54)
Location type (population-based)=1	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Location type (population-based)=2	-2.845**	-0.492	-1.795	-0.589
	(1.02)	(0.66)	(1.24)	(0.58)
Location type (population-based)=3	-2.397*	0.056	2.835*	1.413*
	(1.12)	(0.77)	(1.31)	(0.66)
Water availability	-0.142	0.131	-2.111	
	(0.96)	(0.65)	(1.23)	
Aguascalientes	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Baja California	3.119	2.125	0.280	-0.069
	(3.47)	(2.65)	(4.48)	(2.29)
Baja California Sur	0.283	2.561	-0.908	0.052
	(4.94)	(3.73)	(6.07)	(3.20)
Campeche	3.658	5.804	-1.105	0.678
	(6.04)	(3.51)	(6.13)	(3.06)
Coahuila de Zaragoza	4.333	2.443	-3.105	-1.016
	(3.30)	(2.61)	(4.43)	(2.31)
Colima	3.756	3.020	1.872	-0.611
	(4.65)	(3.58)	(6.60)	(3.14)
Chiapas	3.006	2.967	4.277	5.090*
	(3.72)	(2.77)	(4.45)	(2.35)
Chihuahua	2.413	5.602*	0.091	1.812
	(3.32)	(2.64)	(4.74)	(2.25)

Ciudad de México	5.429	5.113*	2.096	0.206
	(3.25)	(2.43)	(4.66)	(2.12)
Durango	4.738	5.921	-0.214	3.432
	(4.37)	(3.32)	(5.19)	(2.65)
Guanajuato	5.135	1.909	-3.588	-0.964
	(3.13)	(2.52)	(4.23)	(2.18)
Guerrero	7.080*	4.458	-4.156	-1.200
	(3.57)	(2.81)	(4.42)	(2.40)
Hidalgo	9.318*	8.619**	-0.643	3.556
	(3.71)	(3.12)	(4.76)	(2.58)
Jalisco	3.981	3.625	-4.823	-0.411
	(3.11)	(2.44)	(4.22)	(2.11)
México	4.772	2.072	-3.002	0.864
	(2.94)	(2.34)	(3.92)	(2.02)
Michoacán de Ocampo	6.764	5.646*	0.527	4.606*
	(3.47)	(2.61)	(4.36)	(2.25)
Morelos	4.712	-0.314	-0.730	0.391
	(4.03)	(2.91)	(5.88)	(2.52)
Nayarit	4.306	3.171	-1.899	-3.694
	(4.82)	(3.74)	(5.43)	(3.05)
Nuevo León	2.298	2.302	-1.731	-0.626
	(3.34)	(2.51)	(4.15)	(2.16)
Oaxaca	4.089	4.305	2.497	4.098
	(3.67)	(2.81)	(4.56)	(2.44)
Puebla	0.203	1.657	-9.847*	4.188
	(3.25)	(2.58)	(4.36)	(2.17)
Querétaro	5.957	-0.108	-5.205	2.519
	(3.89)	(3.21)	(5.49)	(2.77)
Quintana Roo	0.788	0.643	4.619	-4.020
	(4.24)	(3.02)	(5.72)	(2.68)
San Luis Potosí	3.981	1.816	-1.484	-1.040
	(3.55)	(2.80)	(4.40)	(2.47)
Sinaloa	-0.880	-1.355	-4.786	0.112
	(3.53)	(2.84)	(5.44)	(2.47)
Sonora	3.766	5.172	-0.612	-3.130
	(3.62)	(2.71)	(4.49)	(2.35)
Tabasco	2.881	3.115	5.588	-4.048
	(4.07)	(3.01)	(5.31)	(2.60)
Tamaulipas	5.936	2.219	-1.502	-3.667
	(3.50)	(2.62)	(4.66)	(2.26)
Tlaxcala	7.704	4.525	-3.595	0.585
	(4.16)	(3.13)	(5.75)	(2.71)
Veracruz de Ignacio de la Llave	5.420	-2.100	3.336	4.485*
	(3.18)	(2.56)	(5.02)	(2.17)
Yucatán	8.873*	4.753	-0.999	-0.016
	(4.00)	(2.81)	(4.70)	(2.53)

Zacatecas	3.796	5.074	-1.483	4.898
	(4.25)	(3.28)	(5.38)	(2.81)
Share of Adults Employed	2.453	4.327***	5.087**	5.085***
	(1.39)	(1.16)	(1.76)	(1.11)
Paid worker	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Self-employed	-4.873	-0.594	-5.392	-8.047***
	(2.71)	(1.83)	(3.40)	(1.14)
Unpaid Family Worker	-7.188*	1.468	-8.093	-1.132
	(3.50)	(1.82)	(4.53)	(1.08)
Unpaid Worker in Non-Family Enterprise	2.423	3.226	0.250	-3.478*
	(2.32)	(2.28)	(2.79)	(1.44)
Number of Other Adults		-1.310***		-2.374***
		(0.20)		(0.18)
Graduate studies		5.447*		10.096***
		(2.66)		(1.97)
Head with No Spouse		0.000		0.000
		(.)		(.)
Younger than Head/Spouse		-2.969		-6.540***
		(1.53)		(1.02)
Same Age as Head/Spouse		-3.728		-6.342***
		(2.66)		(1.33)
Older than Head/Spouse		-3.677*		-7.400***
		(1.53)		(1.08)
Head with No Spouse		0.000		0.000
		(.)		(.)
Less Education than Head/Spouse		1.098		-0.569
		(0.82)		(0.72)
Same Education as Head/Spouse		0.065		0.561
		(0.66)		(0.57)
More Education than Head/Spouse		0.000		0.000
		(.)		(.)
Water is available part of the day				-0.879
				(0.54)
constant	-4.990	4.287	-18.521	25.657***
	(8.66)	(4.35)	(10.25)	(3.44)
/				
var(e.hhprod_wh)	95.749***	150.888***	151.490***	307.792***
	(5.02)	(4.34)	(7.70)	(5.31)
Pseudo-R-sqr	0.023	0.020	0.065	0.040
Observations	770	2542	782	6807

Standard Errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table B2 Results of Tobit Regressions of Household Production Weekly Hours by Age and Sex for Rural Areas

	Boys	Men	Girls	Women
Children aged 0 to 2 enrolled	-4.446	-0.290	1.061	-2.016
	(2.63)	(2.39)	(4.35)	(1.95)
Children aged 3 enrolled	-0.687	4.513**	4.921	-0.018
	(2.10)	(1.70)	(3.38)	(1.49)
Number of children aged 4 enrolled in household	6.388**	3.424	-0.911	-1.235
	(2.02)	(1.98)	(3.31)	(1.79)
Number of children aged 5 enrolled in household	0.679	0.043	-0.021	-0.520
	(1.89)	(1.91)	(3.48)	(1.77)
Number of children aged 0 to 2 in household	4.383***	0.178	1.072	4.748***
	(0.97)	(0.67)	(1.63)	(0.64)
Number of children aged 3 in household	2.815	-1.145	-3.754	2.728*
	(1.57)	(1.29)	(2.55)	(1.12)
Number of children aged 4 to 5 in household	-0.753	-1.945	-0.565	1.951
	(1.79)	(1.87)	(3.38)	(1.69)
Number of Adults	-1.007**		-0.320	
	(0.33)		(0.59)	
Married	9.180**	1.243	25.005***	12.216***
	(3.48)	(0.93)	(2.49)	(0.93)
Can you read and write?	12.382*	1.492	0.000	5.372***
	(5.36)	(1.76)	(.)	(1.40)
Primary	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Secondary	-3.572**	3.551**	-1.241	-0.621
	(1.36)	(1.25)	(2.07)	(1.02)
High school	-9.623	5.252***	8.318	-2.995*
	(6.35)	(1.56)	(5.42)	(1.33)
Age	0.711	-0.025	2.130***	-0.061
	(0.38)	(0.04)	(0.63)	(0.03)
Employed	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Not in Labor Force	-1.649	5.716**	0.510	8.231***
	(1.85)	(1.95)	(4.84)	(1.79)
Married Couple with Children	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Female Head	0.009	1.762	3.233	-3.168*
	(1.32)	(1.13)	(1.76)	(1.26)
Male Head	-2.860	-0.261	10.440*	6.665**

	(2.39)	(1.93)	(5.10)	(2.41)
Total current income per capita (income poverty)	-0.000	0.000	-0.000	-0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Stove	2.104	-1.633	-5.808**	-3.100**
	(1.36)	(1.15)	(2.05)	(1.04)
Laundry	1.394	1.811	-1.953	-0.733
	(1.09)	(0.93)	(1.86)	(0.83)
Microwave oven	1.757	7.284	0.000	-2.036
	(12.59)	(12.19)	(.)	(15.41)
iron	1.946	-2.628**	1.318	-0.088
	(1.14)	(1.01)	(1.82)	(0.91)
Blender	-0.242	2.386	-4.997*	1.986
	(1.39)	(1.26)	(1.98)	(1.06)
gas	3.610**	0.243	0.853	3.400***
	(1.29)	(1.09)	(2.12)	(0.97)
Sink	2.394*	-2.255*	2.501	0.940
	(1.15)	(0.94)	(1.73)	(0.87)
Water availability	1.140	0.561	-0.655	
	(0.98)	(0.85)	(1.58)	
Aguascalientes	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Baja California	1.438	4.092	-6.341	-9.319
	(7.76)	(4.25)	(9.47)	(4.91)
Baja California Sur	17.993*	1.753	-12.357	-0.893
	(8.48)	(8.06)	(17.24)	(6.50)
Campeche	0.319	4.352	-4.082	2.391
	(6.73)	(4.99)	(9.69)	(5.01)
Coahuila de Zaragoza	2.094	8.072	-5.885	-4.590
	(5.60)	(4.50)	(8.63)	(4.43)
Colima	0.235	-4.232	-12.708	-2.021
	(11.00)	(8.68)	(15.71)	(9.16)
Chiapas	-0.857	3.016	4.312	3.106
	(4.91)	(3.56)	(6.57)	(3.59)
Chihuahua	5.110	-3.429	-11.969	-1.211
	(6.24)	(5.18)	(7.36)	(4.26)
Ciudad de México		2.902		26.136*
		(8.87)		(10.15)
Durango	6.716	-0.066	-9.549	5.431
	(5.55)	(4.15)	(7.21)	(4.10)
Guanajuato	1.712	1.319	-2.216	-5.830
	(4.93)	(3.50)	(6.83)	(3.60)
Guerrero	3.093	5.618	-1.906	0.881
	(5.00)	(3.69)	(6.93)	(3.74)
Hidalgo	1.316	5.861	-8.419	-0.154
	(5.05)	(3.69)	(7.03)	(3.72)

Jalisco	12.797*	-0.513	-9.174	-1.449
	(5.81)	(5.09)	(10.35)	(3.94)
México	-0.440	11.080**	6.373	-3.710
	(4.90)	(3.55)	(7.29)	(3.60)
Michoacán de Ocampo	-0.366	4.400	-0.052	2.733
	(5.09)	(3.71)	(6.58)	(3.74)
Morelos	9.422	7.241	-9.223	-9.012
	(7.01)	(5.35)	(17.56)	(5.16)
Nayarit	2.283	-4.413	-5.380	-5.132
	(5.59)	(4.73)	(8.58)	(4.47)
Nuevo León	-2.970	-1.972	-10.600	-4.991
	(8.57)	(5.76)	(8.94)	(5.17)
Oaxaca	4.306	12.058**	-2.528	4.065
	(5.00)	(3.65)	(6.80)	(3.64)
Puebla	1.889	2.209	1.357	2.704
	(4.90)	(3.73)	(6.52)	(3.66)
Querétaro	0.815	0.051	-5.317	1.016
	(5.23)	(4.31)	(6.93)	(4.09)
Quintana Roo	-4.612	-3.613	-5.931	-6.275
	(6.17)	(5.64)	(12.19)	(5.14)
San Luis Potosí	-1.410	4.090	-5.548	-3.305
	(5.37)	(3.91)	(7.24)	(3.88)
Sinaloa	0.073	-0.213	-6.247	-2.726
	(5.40)	(3.75)	(7.60)	(3.90)
Sonora	-9.760	5.259	-6.714	-7.293
	(6.04)	(4.16)	(14.60)	(4.41)
Tabasco	1.239	0.395	-4.914	-5.920
	(5.08)	(3.76)	(6.80)	(3.86)
Tamaulipas	0.182	10.735*	-0.373	1.658
	(6.19)	(4.94)	(10.96)	(4.70)
Tlaxcala	4.554	3.167	-1.578	0.504
	(6.26)	(4.68)	(9.27)	(4.98)
Veracruz de Ignacio de la Llave	-1.921	1.923	-2.962	0.639
	(4.96)	(3.50)	(6.49)	(3.56)
Yucatán	0.033	1.580	-10.803	-7.527
	(5.48)	(4.60)	(8.04)	(4.60)
Zacatecas	-0.921	3.616	1.893	3.373
	(5.31)	(4.15)	(7.47)	(4.04)
Share of Adults Employed	1.027	3.451	5.214*	1.926
	(1.50)	(1.84)	(2.40)	(1.65)
Paid worker	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Self-employed	-1.367	1.432	-2.028	-5.881**
	(1.97)	(2.35)	(5.34)	(1.83)
Unpaid Family Worker	-5.125	3.408	9.747	-0.120
	(2.83)	(2.35)	(6.16)	(1.56)

Unpaid Worker in Non-Family Enterprise	-0.348	5.849*	-0.185	-4.389*
	(1.85)	(2.64)	(4.31)	(2.01)
Number of Other Adults		-1.096***		-2.327***
		(0.30)		(0.27)
Undergraduate studies		7.820***		2.938
		(2.07)		(1.86)
Unemployed		9.641*		-6.173
		(4.40)		(11.31)
Head with No Spouse		0.000		0.000
		(.)		(.)
Younger than Head/Spouse		-9.161***		-5.151**
		(2.49)		(1.68)
Same Age as Head/Spouse		-11.975**		-1.570
		(4.35)		(2.22)
Older than Head/Spouse		-10.006***		-5.403**
		(2.50)		(1.83)
Head with No Spouse		0.000		0.000
		(.)		(.)
Less Education than Head/Spouse		4.196**		1.188
		(1.55)		(1.31)
Same Education as Head/Spouse		2.973*		-0.995
		(1.20)		(0.99)
More Education than Head/Spouse		0.000		0.000
		(.)		(.)
Graduate studies				13.008
				(6.86)
Water is available part of the day				1.358
				(0.77)
constant	-18.747*	12.171*	-1.750	38.081***
	(9.20)	(5.83)	(11.81)	(4.98)
var(e.hhprod_wh)	65.468***	130.772***	176.920***	320.083***
	(4.62)	(6.00)	(12.20)	(8.59)
Pseudo-R-sqr	0.037	0.026	0.084	0.040
Observations	407	999	425	2796

Standard Errors in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Table B3 Result of Probit estimates on enrollment of children aged 0 to 3

	Enrollment of 0 to 2 year olds	Enrollment of 3 year olds
Children aged 0 to 2 enrolled		-0.500***
		(0.13)
Children aged 3 enrolled	0.929**	
	(0.33)	
Number of children aged 4 enrolled in household	-0.082	
	(0.37)	
Number of children aged 5 enrolled in household	-0.004	0.267
	(0.38)	(0.17)
Number of children aged 3 in household	-1.476***	
	(0.32)	
Number of children aged 4 to 5 in household	-0.208	-0.422**
	(0.36)	(0.14)
Sex	0.132	-0.041
	(0.15)	(0.14)
Age	0.001	-0.001
	(0.00)	(0.00)
Primary	0.000	0.000
	(.)	(.)
Secondary	0.103	0.084
	(0.10)	(0.08)
High school	0.308**	0.204*
	(0.12)	(0.10)
Undergraduate studies	0.816***	0.370***
	(0.15)	(0.13)
Graduate studies	0.732**	0.373
	(0.24)	(0.24)
Married Couple with Children	0.000	0.000
	(.)	(.)
Female Head	0.198	-0.085
	(0.17)	(0.15)
Male Head	0.692**	0.255
	(0.22)	(0.22)
Total current income per capita (income poverty)	0.000	0.000
	(0.00)	(0.00)
Stove	-0.158	-0.032
	(0.14)	(0.12)
Laundry	0.245*	0.097
	(0.11)	(0.08)
Microwave oven	0.336***	0.152
	(0.10)	(0.09)
iron	0.144	0.039

	(0.10)	(0.09)
Blender	-0.207	-0.106
	(0.12)	(0.09)
gas	0.076	0.065
	(0.13)	(0.11)
Sink	0.010	-0.169*
	(0.14)	(0.08)
Water availability	-0.016	
	(0.11)	
Aguascalientes	0.000	0.000
	(.)	(.)
Baja California	-0.337	0.054
	(0.27)	(0.22)
Baja California Sur	0.278	0.133
	(0.26)	(0.23)
Campeche	0.034	0.459*
	(0.23)	(0.19)
Coahuila de Zaragoza	-0.009	0.160
	(0.21)	(0.20)
Colima	0.327	0.307
	(0.23)	(0.21)
Chiapas	-0.085	0.655***
	(0.26)	(0.19)
Chihuahua	-0.362	0.030
	(0.25)	(0.21)
Ciudad de México	-0.148	0.394
	(0.24)	(0.23)
Durango	0.252	0.278
	(0.22)	(0.20)
Guanajuato	-0.068	0.186
	(0.23)	(0.20)
Guerrero	0.084	0.630**
	(0.23)	(0.20)
Hidalgo	-0.243	0.228
	(0.29)	(0.21)
Jalisco	-0.271	-0.076
	(0.25)	(0.25)
México	-0.533	0.421*
	(0.29)	(0.20)
Michoacán de Ocampo	0.037	0.228
	(0.22)	(0.20)
Morelos	-0.123	-0.080
	(0.25)	(0.23)
Nayarit	0.266	0.374
	(0.22)	(0.20)
Nuevo León	0.010	0.231

	(0.23)	(0.21)
Oaxaca	0.228	0.752***
	(0.24)	(0.19)
Puebla	-0.034	0.568**
	(0.23)	(0.20)
Querétaro	-0.187	0.088
	(0.26)	(0.22)
Quintana Roo	-0.336	0.130
	(0.25)	(0.21)
San Luis Potosí	-0.105	0.623***
	(0.23)	(0.19)
Sinaloa	0.153	0.088
	(0.21)	(0.20)
Sonora	-0.087	0.288
	(0.24)	(0.20)
Tabasco	0.223	0.654***
	(0.22)	(0.19)
Tamaulipas	-0.173	-0.033
	(0.23)	(0.21)
Tlaxcala	-0.005	0.311
	(0.24)	(0.20)
Veracruz de Ignacio de la Llave	0.117	0.092
	(0.31)	(0.24)
Yucatán	0.013	0.429*
	(0.23)	(0.20)
Zacatecas	-0.234	0.350
	(0.23)	(0.19)
Location type (population-based)=1	0.000	0.000
	(.)	(.)
Location type (population-based)=2	-0.188	0.011
	(0.12)	(0.10)
Location type (population-based)=3	-0.333**	0.159
	(0.12)	(0.12)
Location type (population-based)=4	-0.272*	0.159
	(0.12)	(0.11)
Water is available part of the day		0.104***
		(0.07)
constant	-1.597***	-1.484***
	(0.35)	(0.27)
Pseudo-R-sqr	0.200	0.052
Observations	4565	4565

C. Simulation of Employment Impacts of ECE Expansion

In order to estimate the overall effect of the proposed policy intervention, we must consider the employment effects of the additional spending on early childhood education, as well as the changes in time use patterns among households that receive new paid employment as a result. An increase in employment can have counteracting impacts on household wellbeing. Additional income can lift poor households out of income poverty, but the additional hours spent on income-generating activities can increase time deficits within the household and thus lower well-being. The overall direction of these impacts will depend on labor market conditions, as well as household and individual characteristics. In order to estimate these impacts, we implement a multi-part microsimulation model.

The steps required to produce the estimates are as follows. First, we must identify the pool of potential job recipients for the new employment indicated in the macro analysis produced by ONU Mujeres. The latter comprises employment changes by industry. We estimate the occupational structure for each industry by using the existing distribution in the ENIGH. Then for each individual in the recipient pool, we must impute a number of characteristics to be used to match them with a new job: their likeliest industry and occupation of employment; the wages they are likely to receive; and the number of hours they are likely to work. In addition, we must estimate their contribution to family farm and non-farm enterprises, if they work as unpaid family workers. Once we have the necessary information, we perform a hot-deck statistical matching procedure to match each of the potential job recipients with the jobs indicated by the macro analysis. We then compare the earnings the potential recipients would receive to their actual contributions and assign the job if earnings exceed 75 percent of their estimated contributions. This process continues until all jobs are assigned. We move on to reassign household production time for each adult in the households that contain job recipients with another hot-decking statistical matching procedure. Finally, we check that the results are plausible. We detail each step below.

Data and Methodology

The base data sets for the microsimulations presented in this appendix is the synthetic dataset created for the estimation of the LIMTIP for Mexico (the match is documented in Appendix A, above), modified as described in Appendix B above in order to capture the direct effects of the expansion of early childhood education services on the hours spent each week on household production by individuals.

We begin with the aggregate output of the analysis produced by ONU Mujeres (2021), which breaks down direct employment changes into four different sectors and indirect and induced employment changes across all sectors. We apply the existing occupational structure of employment in each industry (as found in the ENIGH 2020). This yields a matrix of new jobs by industry and occupation.

To assign the jobs we use a hot-decking statistical matching procedure. We will describe the latter below, but first we will outline the preparation for this matching procedure. We first identify potential job recipients. These potential recipients are those that are not currently working for pay in Mexico, not retired or in school, and not physically disabled. Next, we identify donor records within the same data set, because we will be assigning sets of job characteristics (industry, occupation, earnings and hours) that actually exist to new job recipients. For all recipients and donors, we rank industries by the likeliness of being employed within them by running a multinomial *probit* model on all of the employed individuals and then using the results to predict the likeliest industries. We repeat this procedure for occupations. Finally, we predict the likelihood of being employed using a simple *probit* model.

We next use a three-stage Heckit procedure to impute wages and hours for each individual. The imputations for the earnings and usual weekly hours of paid work are performed using a three-stage Heckit procedure (Berndt 1996, p. 627), separately for each combination of four age categories,[13] sex, and area of residence. The first stage is a probit estimation of labor force participation:

$$lf_i^* = \alpha_1 + \beta X + \varepsilon_i$$

$$lf_i = 1 \; if \; lf_i^* > 0 \; \& \; \varepsilon_i \sim N(0,1)$$

The vector of explanatory variables, *X*, comprises the number of children aged less than five and the number of children aged six to seventeen in the household, the individual's education, and the individual's spouse's age, education and labor force status. The regression is run on the universe of all eligible adults. The Mills ratio is calculated for all individuals using the results of the first stage regression:

$$\lambda = \frac{f\left(\frac{\widehat{-lf}}{\sigma_{\widehat{lf}}}\right)}{\left(1 - F\left(\frac{\widehat{-lf}}{\sigma_{\widehat{lf}}}\right)\right)}$$

Where *f* is the normal density function, *F* is the normal distribution function, $\hat{lf}$ is the estimated probability of labor force participation, and $\sigma_{\hat{lf}}$ is the standard deviation of $\hat{lf}$.

The second stage is an OLS estimate of the log of hourly wage:

$$lnw_i = \alpha_2 + \gamma_2 Y + \theta_2 \lambda + \mu_i$$

This regression is run only on those that are actually employed for pay. The vector of explanatory variables, *Y*, in this stage includes the individual's education, age, industry, occupation, and state, and finally, λ, the Mills Ratio calculated in the first stage. Inclusion of the Mills Ratio corrects for the selection bias induced by limiting the regression to those in paid employment. The imputed log of wage is predicted for donors and recipients from the results of the regression, with industry and occupation replaced for the latter by the likeliest industries and occupations predicted in the previous step.

The third stage is a regression of usual hours of paid work per week:

$$h_i = \alpha_3 + \gamma_3 Z + \omega ln\widehat{w_i} + \theta_3 \lambda + \eta_i$$

The regression is once again run only on those in paid employment. The vector of explanatory variables, *Z*, in this stage is the same as the previous stage, with the addition of the number of children aged less than five, the number of children aged six to seventeen in the household and spouse's labor force status. Finally, the imputed wage predicted in the second stage and the Mills Ratio calculated in the first stage are included. Imputed hours per week are predicted for donors and recipients using the results of

[13] Less than 25 years old, 25 to 34 years old, 35 to 54 years old, and 55 and older.

the regression, replacing the industry and occupation of the latter with their predicted values as for the wage equation.

With the variables generated in the previous steps, as well as other characteristics, we then proceed through the job assignment procedure. For each industry and occupation pair in turn, for those recipients for whom the industry and occupation were the likeliest we identify a pool of individuals actually employed in that industry and occupation that most resemble each recipient. We randomly draw from this group of donors and assign the job to the recipient. We next check that the sum of the weights of the recipients does not exceed the number of new jobs available. If there are more recipients than jobs, we make the assignment only to those that are the likeliest to be employed (using the results of the probit estimation from the first step), using up all of the available jobs. If there are more jobs than recipients, they are all assigned jobs. The total jobs assigned is then subtracted from the total remaining to be assigned in that cell of the industry/occupation. Those assigned jobs are removed from the remaining recipient pool and the process continues. If after going through all the possible assignments for recipients' first most likely industry and occupation there are still jobs remaining, we move on to the second most likely industry and occupation and repeat the above procedure. This process iterates until all jobs have been assigned

Once the jobs assignment is complete, we address the likelihood of a reshuffling of household production responsibilities in recipient households. We thus go through a second round of statistical matching. In this round, the recipient pool consists of all those for whom time use information is available in household that contain at least one job recipient. The donor pool consists of everyone in the survey. The change in the allocation of time use hinges on the change in the number of workers in the household, so for this round of hot-deck matching we weight the number of male and female workers as heavily as the number of adults and the number of children in the household. In this case, we match within groups of individuals with the same sex, age category and educational attainment.

Finally, we check the results to the best of our ability. This is largely a judgement call since there is no counterfactual distribution with which to compare our estimates. We now move on to document the microsimulation and to report the checks we do to ensure the quality of the microsimulation.

Employment Microsimulation

The employment changes produced by the input-output model used in the ONU Mujeres study are by 4-digit industry. We merge these into jobs by two-digit industry.[14] We then use the occupational distribution for each 2-digit industry to distribute the jobs to occupations. The resulting matrix of employment changes is presented in Table C1, below. The single largest change is in the construction industry, reflecting the large investment in building new facilities for the expansion of early childhood education being modeled here. Employment increases in the facilities themselves are divided into workers in *guarderias* (childcare centers) recorded in the health care and social assistance industry (which grows nearly as much as the construction industry), in pre-schools in the educational services industry and in both areas in the hotel and restaurant industry, representing the food preparation for the children in the facilities. A total of 3.9 million jobs are created in this scenario.

[14] The number of observations in the ENIGH is inadequate to perform a simulation at the four-digit industry level.

Table C1 Changes in Employment by Industry and Occupation

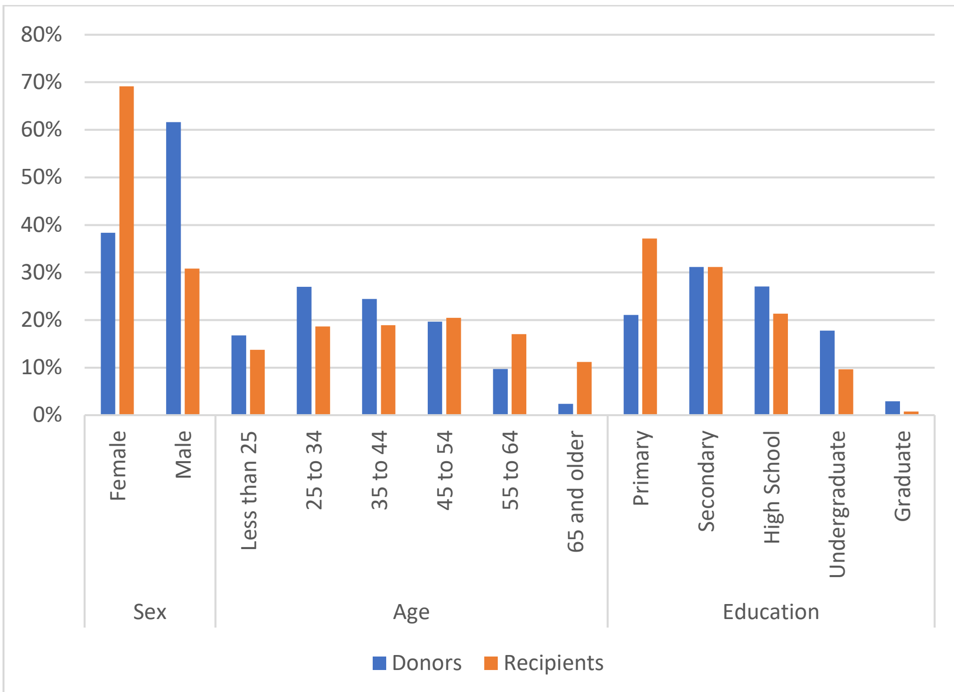
	Directors and Managers	Professionals and Technicians	Adminis -trative workers	Sales persons	Personal services and security	Agriculture workers	Artisan workers	Machine operators drivers and transport workers	Basic support activities
Agriculture, Forestry, Fishing and Hunting	774	1694	530	539	979	102943	292	980	89453
Mining	1581	6641	1654	77	1083	0	5171	7705	7859
Utilities	826	2685	1489	21	167	0	1000	1725	1478
Construction	19988	59890	10290	1838	3666	35	295272	19740	460920
Manufacturing - Food and Apparel	2289	4061	3042	7244	757	452	44872	16606	23060
Manufacturing - Wood, Chemical, and Plastics	3318	8147	4784	3175	916	336	18270	18948	17330
Manufacturing - Metal, Machinery, and Equipment	3216	8977	3573	1587	362	2	11773	39463	14741
Wholesale trade	10878	17576	21831	63524	2014	2254	6890	31170	32383
Retail trade	6227	5065	13785	132768	1390	176	5468	5104	26313
Transportation	1540	2058	3045	84	368	0	136	27842	2682
Postal services and warehousing	151	132	772	12	16	0	0	1342	523
Information	1301	5097	1643	1597	115	0	71	257	692
Finance and Insurance	1780	2954	3640	5005	35	0	0	88	168
Real Estate and Rental and Leasing	13806	23508	14010	48837	10541	46	5235	7052	17693
Professional, Scientific, and Technical Services	2396	19843	2381	652	121	0	365	252	884
Management of Companies and Enterprises	222	744	149	0	0	0	0	0	193

Administrative and Support and Waste Management and Remediation Services	4753	12936	13040	3616	38671	94	622	2795	36673
Educational Services	11845	121115	11002	481	4816	24	371	205	8083
Health Care and Social Assistance	34483	643638	111761	3001	41307	0	1803	4247	55898
Arts, Entertainment, and Recreation	1240	7250	1116	571	1365	71	57	49	2056
Accommodation and Food Services	14334	10107	21806	9246	241706	148	51851	16157	218738
Other Services (except Public Administration)	1828	18700	2570	817	20238	198	7944	1548	61748
Public Administration	1924	4239	3168	6	2226	18	174	303	895

Source: author’s calculations

We first form the recipient and donor pools for the job assignment matching procedure. The recipient pool for the job assignment was defined to comprise all eligible adults[15] that were not already working in paid employment. As is to be expected the recipient and donor pools are quite different (see Figure C1, below). The recipient pool is mostly female (69 percent), while the donor pool is mostly male (62 percent). The recipient pool is more evenly distributed than the donor pool by age, but as such, it is generally older, with 28 percent of the recipients but just 12 percent of donors 55 or older. The donor pool is more educated, with 21 percent having just a primary education, compared to 37 percent of the recipient pool.

Figure C1 Composition of Donor and recipient Pools, by Sex, Age, and Education (Percent)



Source: author's calculations

The assignment itself uses the likeliest sector for each individual in the recipient pool, matching them with donors working in that sector wherever possible. The actual assignment of individuals into industries is compared to their likeliest industry in Table C2, below. Because the composition of the jobs created is entirely in the four industries above, only 18.5 percent of individual job recipients received jobs in their likeliest predicted sector (bolded). Notice that very few recipients' likeliest industry was health and social assistance, in which the bulk of the jobs in the ECE sector are created. Most of those for whom the educational services industry was the likeliest wound up with jobs in the health care and social assistance industry instead. Given the fact that the distribution of jobs created is so different than the existing distribution of jobs (in other words, a very small ECE sector), this pattern of assignments is inevitable and likely to be the best that can be done.

[15] Eligible adults were defined as those between the age of 18 and 74 that were not retired, disabled, or in school, except if they are engaged in paid employment.

Table C2 Comparison of assigned versus likeliest industries for simulation job recipients

	Predicted Likeliest Industry												
Assigned Industry	11	23	31	33	46	48	54	61	62	72	81	93	Total
11 Agriculture, Forestry, Fishing and Hunting	107,758	70,513	0	4,250	0	100	0	0	0	0	1,228	11,996	195,845
21 Mining	9,022	0	0	0	0	0	0	361	0	0	0	353	9,736
22 Utilities	355	0	0	0	0	0	0	6,583	0	0	0	482	7,420
23 Construction	341,781	162,534	1,289	272,276	55,088	8,873	0	3,342	0	0	11,911	12,148	869,242
31 Manufacturing - Food and Apparel	0	57,827	8,926	1,958	29,800	0	0	572	0	0	938	0	100,021
32 Manufacturing - Wood, Chemical, and Plastics	9,702	1,589	0	37,430	14,960	0	0	6,541	0	0	0	328	70,550
33 Manufacturing - Metal, Machinery, and Equipment	16,136	8,034	9,177	28,009	3,271	8,394	0	0	0	0	0	8,214	81,235
43 Wholesale trade	69,349	7,829	0	34,451	55,533	0	0	8,038	0	0	0	10,896	186,096
46 Retail trade	0	0	0	0	194,110	0	0	0	0	0	0	0	194,110
48 Transportation	0	16,410	0	2,167	8,984	4,867	0	0	0	0	0	2,355	34,783
49 Postal services and warehousing	0	0	0	1,182	0	0	0	0	0	0	0	0	1,182
51 Information	0	0	0	0	0	0	1,040	6,738	0	0	0	0	7,778
52 Finance and Insurance	0	0	0	0	0	0	0	9,611	0	0	0	0	9,611
53 Real Estate and Rental and Leasing	582	7,174	0	0	509	0	0	15,382	0	66,969	34,731	13,473	138,820
54 Professional, Scientific, and Technical Services	0	0	0	0	17,589	0	1,296	4,190	0	0	0	0	23,075
55 Management of Companies and Enterprises	0	0	0	0	0	0	0	741	0	0	0	0	741
56 Administrative and Support Services	0	0	0	2,913	26,385	16,702	0	0	0	0	40,797	20,627	107,424
61 Educational Services	2,471	0	0	9,977	6,340	0	1,368	67,199	0	0	0	68,167	155,522
62 Health Care and Social Assistance	0	0	0	17,047	100,904	0	19,674	741,826	5,844	0	8,284	895	894,474
71 Arts, Entertainment, and Recreation	0	1,030	0	1,681	4,634	0	0	0	0	0	0	3,622	10,967
72 Accommodation and Food Services	5,054	43,920	0	24,898	204,042	0	0	242	0	61,257	238,159	5,722	583,294
81 Other Services (except Public Administration)	0	728	0	0	59,869	787	0	0	0	0	50,692	1,669	113,745
93 Public Administration	0	0	0	0	0	0	0	0	0	0	0	10,642	10,642
Total	562,210	377,588	19,392	438,239	782,018	39,723	23,378	871,366	5,844	128,226	386,740	171,589	3,806,313

Source: author's calculations

In order to assess the quality of the matching procedure, we compare the earnings and weekly hours of the recipients to that of the donor pool. While we do not expect these distributions to be necessarily alike, given the nature of the differences between the recipient and donor pools, we still expect there to be some correspondence between them. Figure C2 (below) shows the ratios of mean and median earnings and weekly hours of recipients to donors, by sex and area of residence. It is notable that for the most part, earnings and hours are higher for those receiving jobs in the simulation, especially for urban women. This implies that women are receiving jobs in the higher paying end of the existing job distribution for women. The fact that the hours are higher in the recipient jobs means that a greater share of the assigned jobs are full-time employment. It also implies that there will be larger effects on time use in recipient households.

Figure C2 Ratio of Simulated to Actual Mean and Median Earnings and Weekly Hours by Sex and Area of Residence

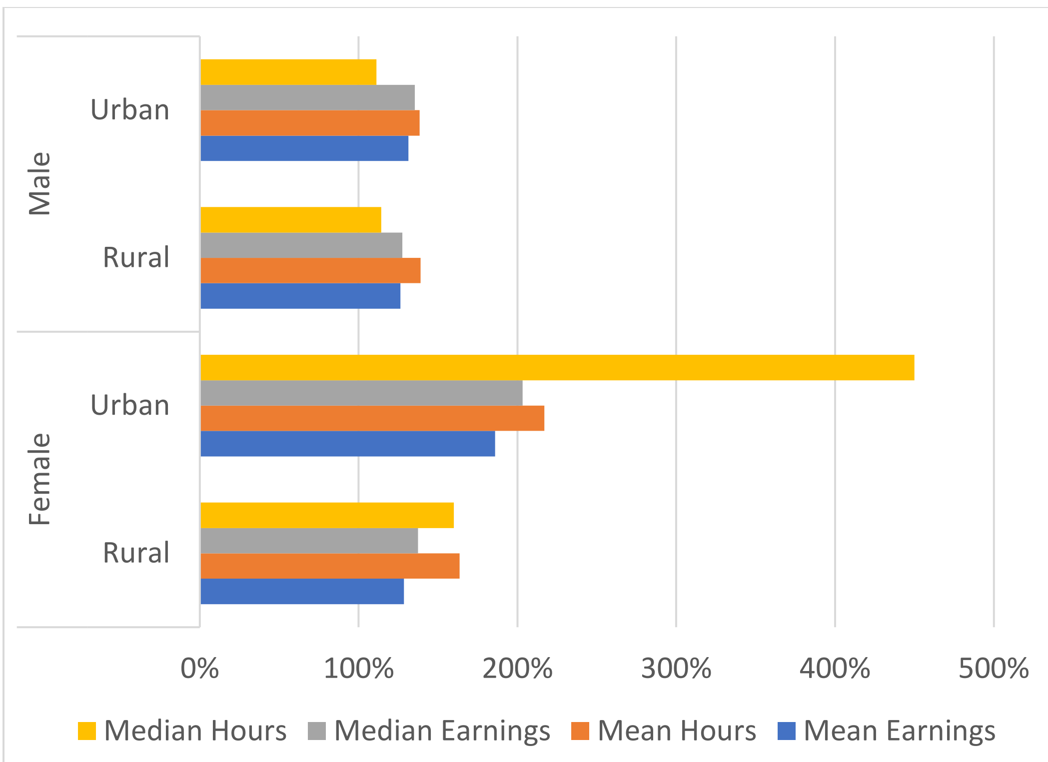
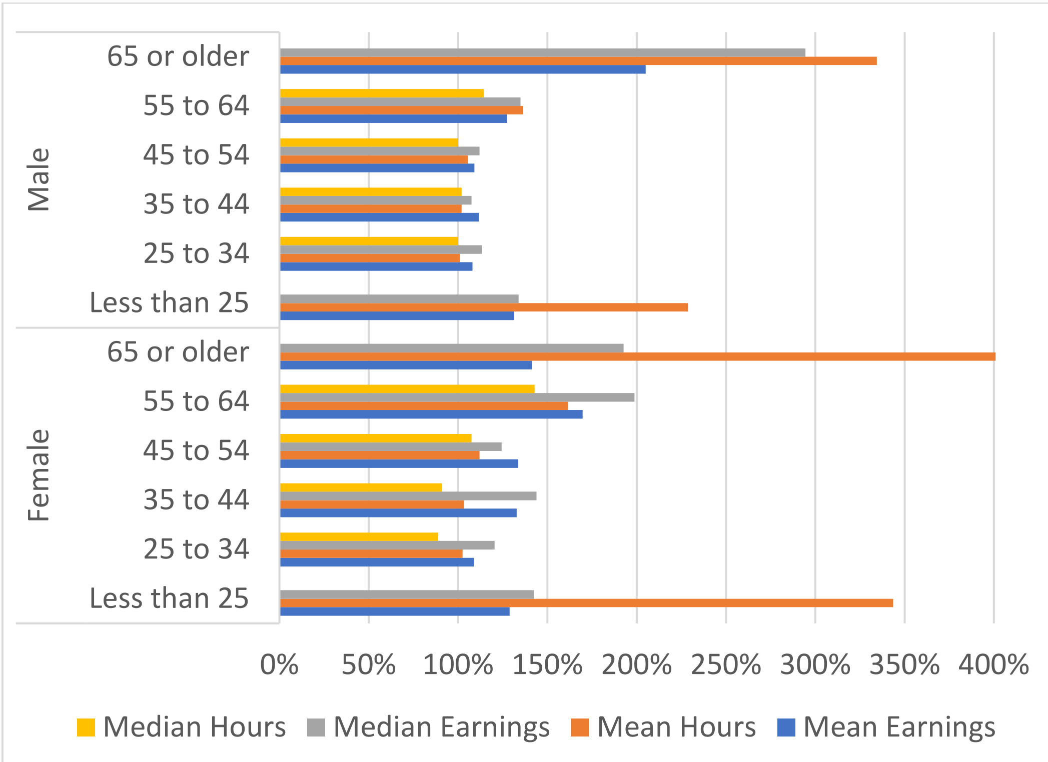


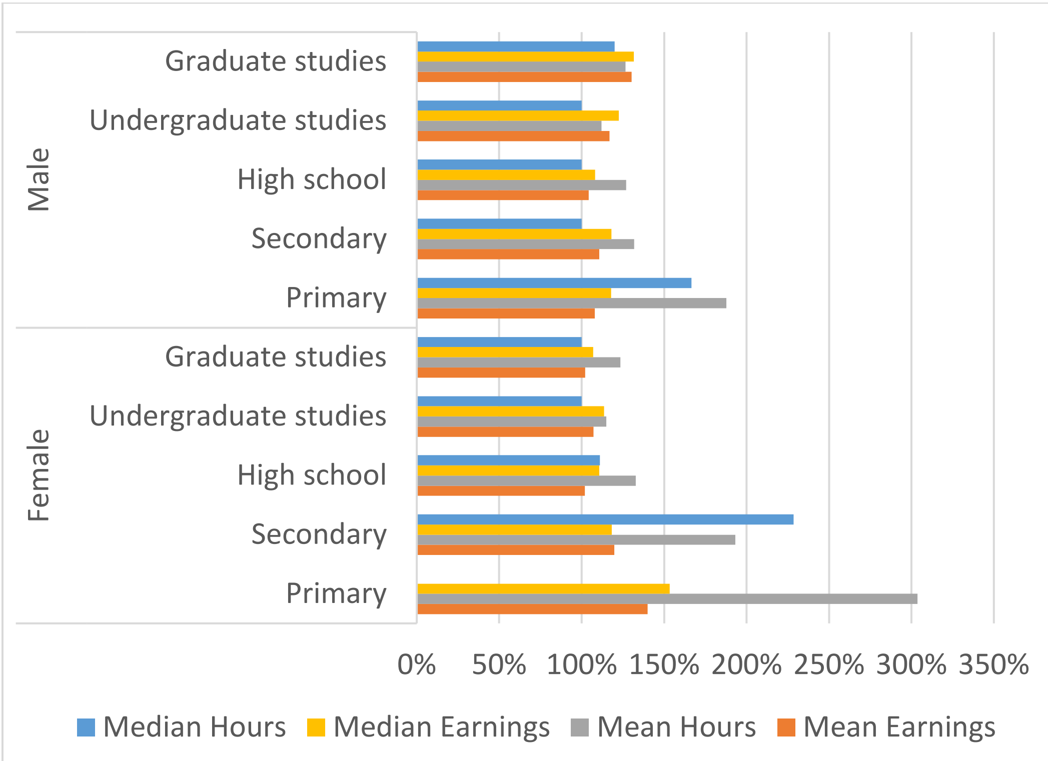
Figure C3 (below) shows the same ratios for male and female recipients by age categories. Mean and median hours are similar for the recipients in the prime working age categories. Male recipients in these age categories also have similar earnings to those in the donor pool, while female recipients' earnings are slightly higher. There are much larger differences between older and younger recipients and donors, due to very low hours and earnings in those groups, particularly for older women (mean weekly hours of income-generating activities for women 65 and older is 4 hours among the donors).

Figure C3 Ratio of Simulated to Actual Mean and Median Earnings and Weekly Hours by Sex and Age



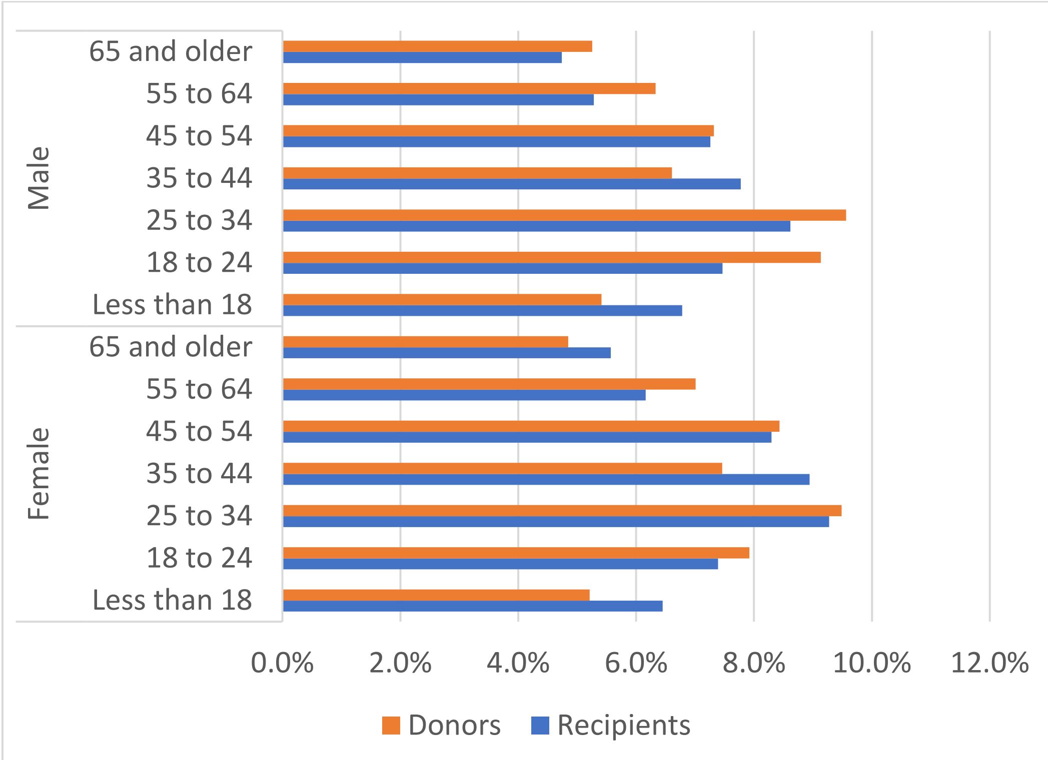
Finally, Figure C4 shows the same ratios by sex and educational attainment. Here we see that the overall differences seen above are largely among those with primary education or less. For these individuals, the jobs produced by the policy intervention are more likely to be full-time than the jobs persons with this level of educational attainment typically have in Mexico. For women, the ratios of earnings are higher among recipients at lower levels of the educational attainment scale, while for men, the opposite is true.

Figure C4 Ratio of Simulated to Actual Mean and Median Earnings and Weekly Hours by Sex and Educational Attainment



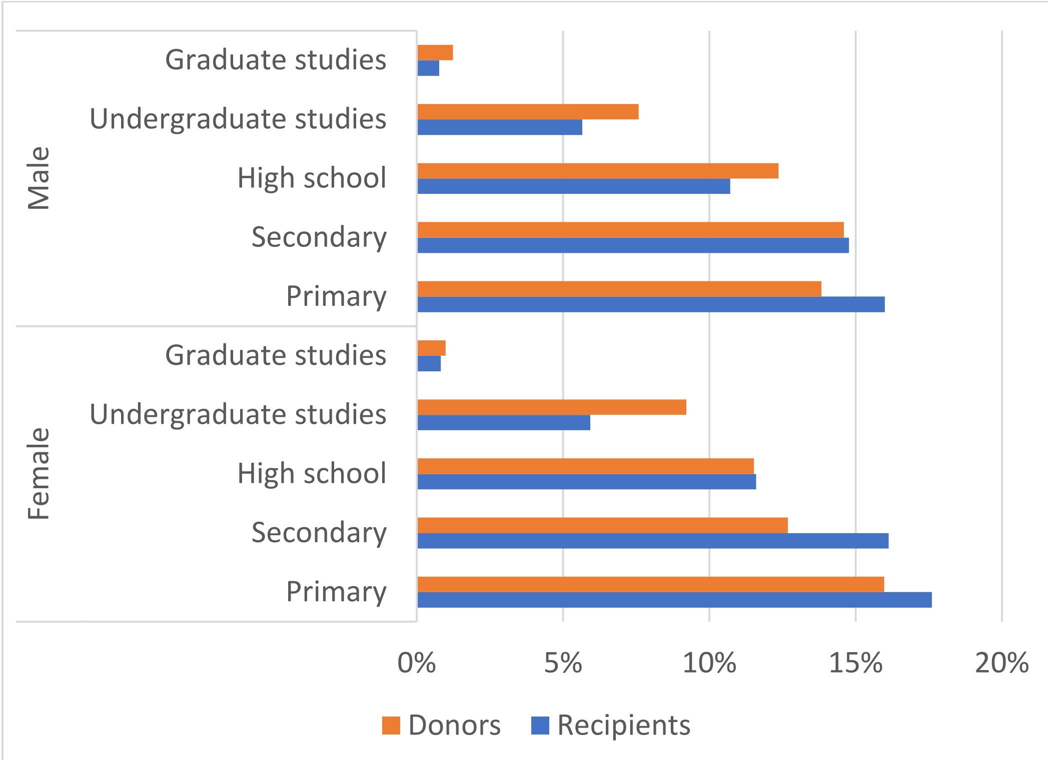
Once the jobs have been assigned, we move on to reassigning household production hours. Since the ENUT collects data for everyone in the household aged 12 and up, the recipient pool is every individual aged 12 and older in a household in which there is a job recipient in the microsimulation. The donor pool is all individuals for whom time use data is collected. We expect the two pools to be similar, with the qualification that the recipient pool will be different to the degree that the households from which job recipients are drawn are different from those in the population as a whole. Figure C5, below, provides the comparison of the recipient and donor pools by sex and age category. Recipients are more concentrated among those between 18 and 34 years old as well as 55 and over.

Figure C5 Time Use Donor and Recipient Pools by Sex and Age



We next compare the distribution of the donor and recipient pools by sex and educational attainment (see Figure C6, below). The interesting characteristic here is that recipients tend to be more educated than the overall population. This inverts the pattern in the recipient pool for the jobs assignment (Figure C1, above). While these differences are interesting, they are not worrying for the reassignment of time use, since that happens within matching cells comprised of individuals with the same age, sex and educational characteristics. We now look at the results of this step of matching.

Figure C6 Time Use Donor and Recipient Pools by Sex and Educational Attainment



To assess the plausibility of the distribution of weekly household production hours in the reassigned households, we first compare the mean and median weekly hours of household production by sex and age (see Figure C7, below). The distribution of hours is quite similar. The largest divergence (24 percent) is in the median weekly hours of household production for females under 18 in the recipient pool, and this does translate to 7 hours per week. It appears that by age and sex, the recipient distribution is quite like that of the donor pool. We see a similar story when we compare the same ratios by sex and educational attainment (see Figure C.8, below). In every sub-group, the ratio of recipient to donor is nearly unity. Here, the largest deviation is 10 percent, among males with graduate education. However, the absolute difference is just 1.2 hours per week.

Figure C7 The Ratio of Mean and Median Weekly Hours of Household Production between Recipients and Donors by Sex and Age

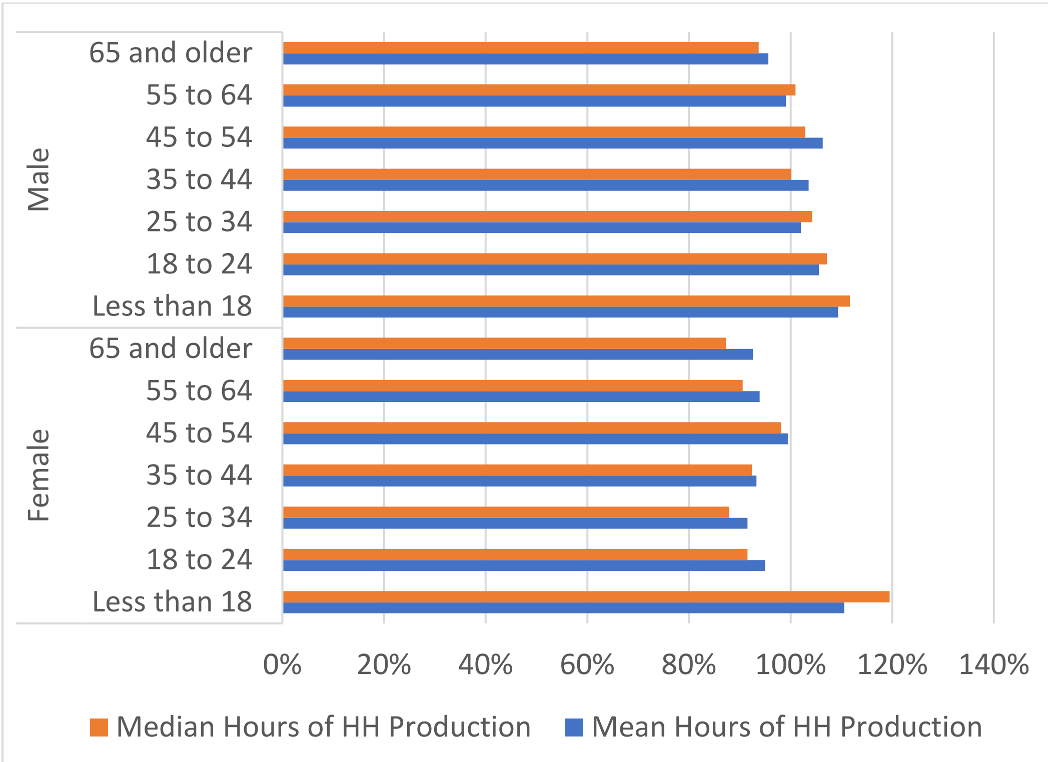
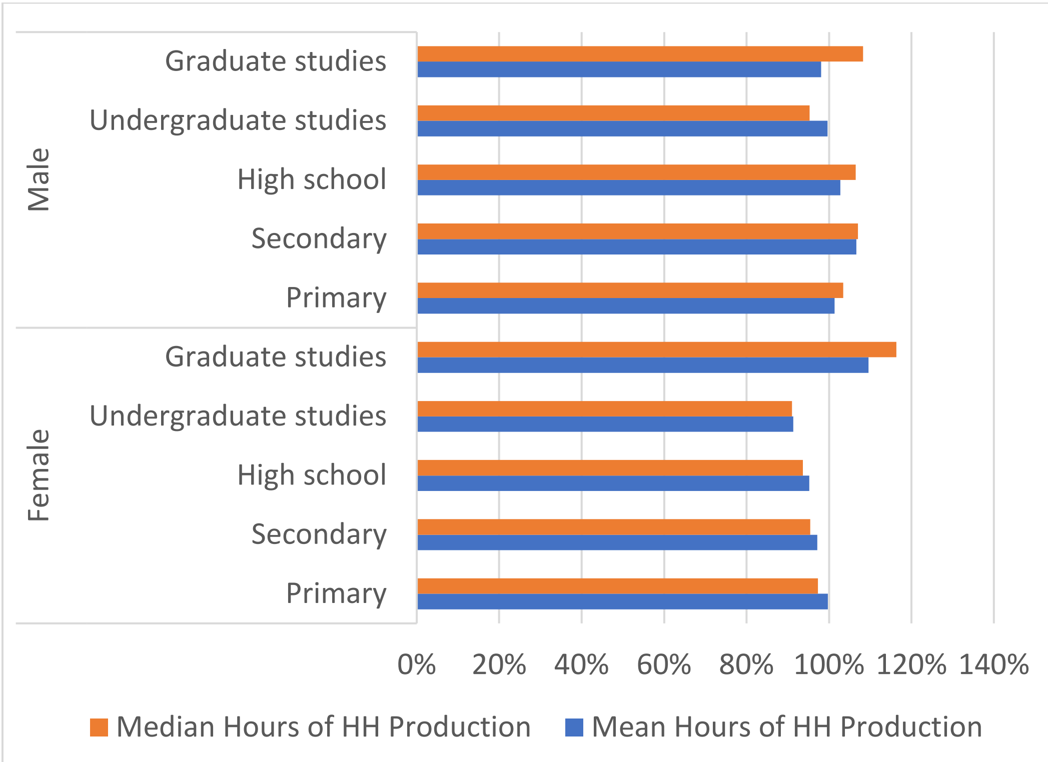


Figure C8 The Ratio of Mean and Median Weekly Hours of Household Production between Recipients and Donors by Sex and Educational Attainment



In short, the simulation appears to produce reasonable results. The employment simulation produces relatively high-paying jobs for less-educated women, which will reduce overall earnings inequality and should reduce income poverty as well.