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Article

Impact of the Information and Communications Technologies (ICT) infrastructure on the returns to higher education in Mexico: A gender analysis

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Abstract: This paper aims to analyze the impact of access to Information and Communication Technologies (ICT) on the private returns to higher education (HE) focusing on gender inequality in 2020. **Methodology:** To evaluate the above impact a set of Mincerian equations will be estimated. The proposed approach mitigates biases associated with self-selection and individual heterogeneity. **Data:** The database comes from the National Household Income and Expenditure Survey (Encuesta Nacional de Ingresos y Gastos de los Hogares, ENIGH) from 2020. **Results:** Empirical evidence suggests that individuals that have HE have a positive and greater impact on their salary income compared to those with a lower educational level, being women that do not have access to ICT those with the lowest wage return. **Policy:** Access to ICT should be considered as one of the criteria that integrate social deprivation in the measurement of multidimensional poverty. Likewise, it is necessary to design public policies that promote the strengthening and creation of educational and/or training systems in technological matters for women. **Limitations:** No distinction was made between individuals that graduated from public or private schools, nor was income from sources other than work considered. **Originality:** This investigation evaluates the impact of access to ICT on the returns to higher education in Mexico, in 2020, addressing gender disparity.

Keywords: returns to higher education; information and communication technologies; gender
JEL Classification: C21; I21; O33

1. Introduction

In recent years, the global labor market has experienced significant disruptions, with Mexico being no exception. Employment opportunities and disposable income have declined, making it increasingly difficult for many to meet basic needs such as food and other essential expenses. A particularly critical period in Mexico occurred between April 2020 and March 2021, marked by a notable decrease in formal employment. **Figure 1** illustrates the number of jobs affiliated with the Mexican Social Security Institute (Instituto Mexicano del Seguro Social, IMSS, 2021) across different federal entities (states).

To illustrate the impact before the pandemic, in March 2020, the IMSS (2021) had 20,482,943 registered workers. By July 2020, during the most critical period, this number decreased to 19,495,952, representing a loss of 986,991 jobs. This reduction in labor income serves as the foundational indicator for analyzing the impact of access to Information and Communication Technologies (ICT) on the returns to higher education (HE) in Mexico.

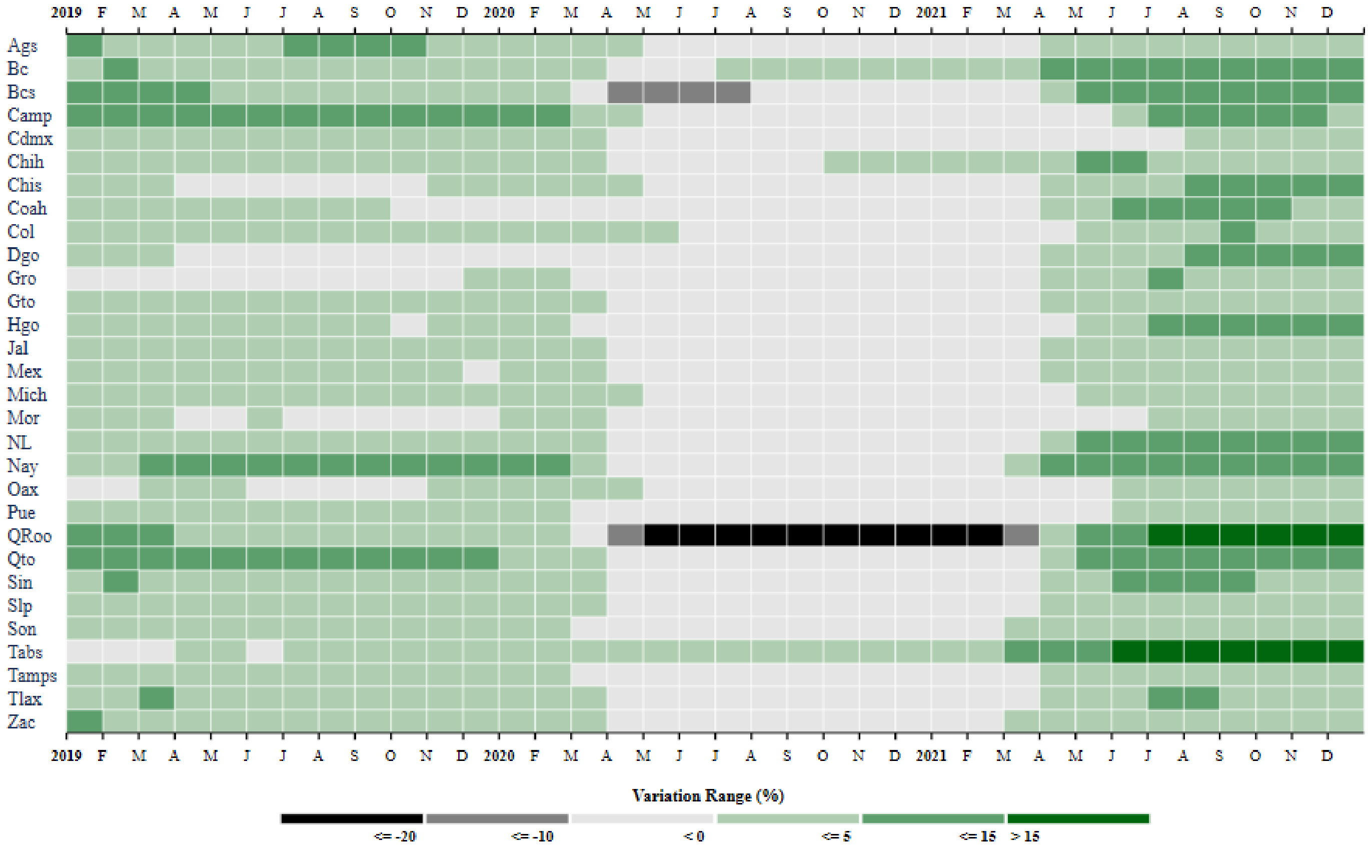

Figure 1. Jobs affiliated with the IMSS by federal entity (state).

(Annual Percentage Variation January 2019–December 2021).

Source: Own elaboration with data from the IMSS (2021. Aguascalientes (Ags), Baja California (Bc), Baja California Sur (Bcs), Campeche (Camp), Coahuila (Coah), Colima (Col), Chiapas (Chis), Chihuahua (Chih), Ciudad de México (Cdmx), Durango (Dgo), Guanajuato (Gto), Guerrero (Gro), Hidalgo (Hgo), Jalisco (Jal), Estado de México (Mex), Michoacán (Mich), Morelos (Mor), Nayarit (Nay), Nuevo León (NL), Oaxaca (Oax), Puebla (Pue), Querétaro (Qto), Quintana Roo (Qroo), San Luis Potosí (Slp), Sinaloa (Sin), Sonora (Son), Tabasco (Tabs),Tamaulipas (Tamps), Tlaxcala (Tlax). Veracruz (Ver), Yucatán (Yuc), Zacatecas (Zac).

On the other hand, the National Council for the Evaluation of Social Development Policy (Consejo Nacional de Evaluación de la Política de Desarrollo Social, CONEVAL) defines two poverty lines: the Extreme Poverty Line by Income (EPLI), which covers the cost of staple foods, and the Poverty Line by Income (PLI), which includes the monetary value of staple foods, goods and services. These thresholds are specified for both rural and urban areas, with the urban EPLI set at $1702.28 and the rural at $1299.30. The urban PLI was $3559.88, while the rural PLI stood at $2520.16.

Table 1 details the sources that make up the total income per capita: monetary and non-monetary income. Column b1 shows the average per capita labor income by income deciles, revealing significant inequality in the distribution of labor income. The first six deciles concentrate the population living in poverty, as defined by the established poverty lines and various social deprivations.

Table 1. Average total current income per capita by source and income decile, 2020 (August 2020 prices).

Decile	Total People in poverty	Total current income (a) = (b) + (c)	Total monetary current income (b) = (b1) + (b2) + (b3)	Labor Income (b1)	Rental income (b2)	Income from transfers (b3)	Total non-monetary current income (c) = (c1) + (c2)	Payment in kind (c1)	Transfers in kind (c2)	Reduction (d) = (b1) − (a)	% of total current income (e) = [(d)/(a)] × 100
I	12,286,095	778.9	737.1	549.3	3.1	184.8	41.9	5.8	36.1	−229.7	−29.5%
II	11,694,859	1453.6	1380.8	1096.3	9.6	274.8	72.9	16.2	56.7	−357.3	−24.6%
III	10,892,850	1923.4	1822.6	1478.7	8.3	335.7	100.8	24.7	76.1	−444.7	−23.1%
IV	9,461,668	2377.1	2257.1	1856.7	13.2	387.2	120.1	32.9	87.1	−520.4	−21.9%
V	6,921,150	2871.5	2719.9	2266.6	14.0	439.3	151.6	44.7	106.8	−604.9	−21.1%
VI	4,397,603	3448.0	3255.2	2730.0	23.2	501.9	192.8	64.8	128.0	−718.0	−20.8%
VII	0	4178.8	3945.1	3306.7	26.5	611.9	233.7	85.7	148.0	−872.0	−20.9%
VIII	0	5236.7	4934.8	4123.9	44.9	766.1	301.9	121.3	180.6	−1112.8	−21.2%
IX	0	7074.1	6688.8	5540.6	69.4	1078.9	385.3	142.0	243.3	−1533.5	−21.7%
X	0	15,812.8	15,082.4	11,885.5	341.0	2856.0	730.3	254.7	475.7	−3927.3	−24.8%
Total	55,654,225	4514.7	4281.7	3482.9	55.3	743.5	233.1	79.3	153.8	−1031.9	−22.9%

Source: Own elaboration with data from the CONEVAL (2020).
Note: Urban income poverty line = $3559.88 and rural income poverty line = $2520.16.

During 2020, non-wage income (columns b2, b3, and c) was an important source for Mexican households. When this income is excluded (column d), a drastic increase in the number of people in poverty is observed. Column e shows that for decile 1 the deductions account for a 29.5% reduction in total income, while for decile 10 the reduction reaches 24.8%. Based on labor income (column b1), the urban PLI of $3559.88 covers up to decile 7, thus adding the largest number of people in poverty.

CONEVAL (2020) reports that out of 126.7 million Mexicans, 55.65 million (43.91%) lived in poverty, with 44.86 million (35.40%) moderately poor and 10.79 million (8.52%) in extreme poverty. Consequently, there is an urgent need for public policies in education aimed at improving salary returns. The most affected during the pandemic were those in poverty without access to ICT for continuing their education. This study underscores the necessity of enhancing and developing more equitable educational systems, where access to ICT is considered not only a short-term investment but also a policy for improving well-being throughout an individual's productive life cycle.

On the other hand, **Table 2** describes the situation in Mexico, from 2015 to 2020, regarding ICT availability and usage, such as computers, internet, television, cell phones, radio, and electricity. According to the National Survey on Availability and Use of ICT (Encuesta Nacional sobre Disponibilidad y Uso de Tecnologías de la Información en los Hogares, ENDUTIH) conducted by the National Institute of Statistics and Geography (Instituto Nacional de Estadística, Geografía e Informática, INEGI), in 2020, 15,615,290 Mexican households had a computer, equivalent to only 43.8% of total households with access to this technology.

It can be observed in **Table 2** that, in 2020, only 59.9% of Mexican households had access to the internet, 91.4% had a television, 42.6% had cable TV, 93.7% had a cell phone, 51.4% had access to the radio, and 99.5% used electricity. **Table 3** shows that, in 2020, of the total population aged six or older in 2020, 43,534,080 were computer users (37.5%), while 82,978,847 (71.5%) and 87,218,465 (75.1%) were internet and cell phone users, respectively.

The primary objective of this article is to conduct a detailed and comparative analysis of the impact of ICT access on the private return to HE in Mexico, focusing on income inequality and educational attainment to explore potential gender gaps. The theoretical framework for this investigation is provided by Mincer's (1974) human capital model, recently expanded by Hasebe (2020).

The distinguish aspects of this research within the context of Mexico include: 1) assesses the impact of ICT access on the private returns to HE with a focus on gender inequality using a sample of 12,376 individuals, 2) considers additional factors such as parental education and household size that may play a role in creating gender gaps, and 3) provides policy recommendations to mitigate labor inequality.

Table 2. Households with information and communications technology equipment, according to type of technology, 2015 to 2020.

Year	Computer users		Internet users		TV		PayTV		Telephonya		Radio		Electric power	
	Absolute	**%**	**Absolute**	**%**	**Absolute**	**%**	**Absolute**	**%**	**Absolute**	**%**	**Absolute**	**%**	**Absolute**	**%**
2015	14,421,344	45	12,568,849	39	30,074,052	93	14,057,196	44	28,699,186	90	21,189,369	66	31,881,286	99
2016	14,901,285	45	15,366,229	47	30,514,307	93	17,046,792	52	29,519,236	90	20,174,609	61	32,573,151	99
2017	15,236,383	45	17,055,332	51	31,374,796	93	16,615,920	50	30,899,589	92	19,733,322	59	33,466,774	99
2018	15,285,544	45	17,974,537	52	31,797,539	93	16,136,639	47	31,514,864	92	19,214,781	56	33,993,049	99
2019	15,504,747	44	19,690,264	56	32,593,577	92	16,089,334	46	32,596,321	92	18,956,235	54	35,089,842	99
2020	15,615,290	44	21,388,838	60	32,623,761	91	15,204,364	43	33,422,743	94	18,328,729	51	35,507,606	99

Source: Own elaboration with data from the ENDUTIH (2020); INEGI (2020).

Note: Includes fixed and/or cellular telephony.

Table 3. Information technology users, 2015–2020.

Year	Computer users		Internet users		Cell phone users	
	Absolute	%	Absolute	%	Absolute	%
2015	54,783,584	51	61,358,202	57	76,369,882	71
2016	50,767,421	47	64,361,129	59	79,690,765	73
2017	49,826,347	45	70,289,609	64	79,587,494	72
2018	49,935,658	45	73,142,199	65	81,865,019	73
2019	48,362,012	42	79,489,450	70	85,549,900	75
2020	43,534,080	37	82,978,847	71	87,218,465	75

Source: Own elaboration with data from the ENDUTIH (2020); INEGI (2020).
Population six years or older. Includes fixed and/or cellular telephony.

The structure of this paper is as follows: section 2 reviews the relevant literature on educational return and the impact of ICT on returns to HE; section 3 describes the methodology used to estimate private returns to HE; section 4 details the dataset used in the research; section 5 presents the results of the econometric estimates carried out; section 6 provides a general discussion on the empirical results obtained; and finally, section 7 gives the conclusion and provides gender-focused public policies aimed at HE considering the use of ICT in Mexico.

2. A short literature review

Among some of the studies that analyze the returns to education are Hansen (1963), Hanoch (1967), McMahon (1991), Psacharopoulos (1993), Ashenfelter and Krueger (1994), Altonji (1993), Altonji and Dunn (1996), Harmon and Walter (1995), Alba-Ramírez and San Segundo (1995), Cohn and Addison (1998), Card (1999), Asplund and Pereira (1999), Card (2000), Harmon et al. (2001), Walter and Nielsen (2001), Carneiro et al. (2001), Psacharopoulos and Patrinos (2002), San Segundo and Valiente (2003), Harmon et al. (2003), Carneiro et al. (2003), Arrazola et al. (2003), and Moffitt (2007).

In particular, for the Mexican case, there are several investigations regarding returns to education, for example: Austria-Carlos and Venegas-Martínez (2011) and Austria-Carlos et al. (2018), Carnoy (1967), Bracho and Zamudio (1994a) and (1994b), Zamudio (1995), Rojas et al. (2000), Barceinas (2001), Sarimaña (2002), Del Razo (2003), Rodríguez-Oreggia (2004), López-Acevedo (2004), Ordaz (2007), and Aguirre-Aguirre et al. (2023).

Meanwhile, the existing literature on the development of ICT demonstrates that access to them generates greater economic development, as in the case of various African countries studied by Ofori et al. (2021), Karakara and Osabuohien (2021), Maeyen and Klyton (2020), Ambe (2018), and Opiyo et al. (2020). Likewise, Pradhan et al. (2022) conducted a similar study in a sample of low- and middle-income countries. Also, Ximei et al. (2022) analyzed South Asia. Finally, in the case of China, there are several studies as those by Feng et al. (2022), Chen and Ye (2021), Min et al. (2020), and Wang and Qi (2021).

The support that ICT represent for refugees and migrants through digital platforms was also analyzed in Bock et al. (2020). In the European case, authors such as Ramírez-García et al. (2018) determined that the creation of APPs for on-the-job training impacts wage improvement. Stamenković et al. (2021) showed that ICT have become a determining factor in generating socioeconomic prosperity in 37 European countries. In the case of Extremadura, Spain, Fernández-Portillo et al. (2020) analyzed the impact of ICT on increasing company income through sales.

In the case of Latin America, Vega (2019) analyzed the association of ICT with poverty in Peru, and Ochoa and Jijón (2022) analyzed the impact of ICT on the financial structure of companies in the communication sector of Guayaquil, Ecuador. Likewise, Marín-Díaz (2019) determined that young people’s access to ICT improves their income in Colombia, while Costa et al. (2018) and Linthon-Delgado and Méndez-Heras (2022) analyzed the importance of ICT in business management and the gender wage gap in Ecuador. In the case of Mexico, Torres-García and Ochoa-Adame (2018) and Moreno and Cuellar (2021) studied the impact of ICT on wage differences and the gender employment gap.

3. Methodology

This study assesses the impact of HE on wage returns, with a particular focus on the role of ICT access with a gender perspective. To estimate the returns to HE, this study utilizes the two-stage process suggested by Heckman et al. (2000) and Heckman et al. (2001) to address biases inherent in the Ordinary Least Squares (OLS) approach. This approach mitigates biases associated with self-selection and individual heterogeneity identified by Card (1999): one related to the correlation between schooling and income, and the other to individuals’ abilities, captured in the regression intercept and correlated with schooling. Likewise, Diez de Medina (1992) highlights that self-selection bias is prevalent in program impact evaluations, especially in quasi-experimental methods. This bias arises when the sample is not randomly selected, either due to the extraction method or the characteristics of the individuals, or both. In random sampling, prior probability information is available, and a larger sample improves estimates. However, non-random samples only allow for the description of the sample characteristics, not the population. In contrast, quasi-experimental designs seek to create a control group using econometric techniques with external data, ensuring initial equivalence of the treatment and control groups, thereby addressing self-selection bias and potential validity issues.

This study compares a treatment group (individuals with HE) to a control group (individuals without HE). Following Baker (2000), the proposed methodology identifies observable differences between the groups and assesses how these differences can be attributed to educational level (treatment) and labor income (outcome), thereby minimizing bias. Therefore, to estimate the impact of access to ICT, a counterfactual scenario is simulated, that is, what would have happened if the HE program had never been implemented. This analysis will allow separating the effects of such involvement from other factors that could influence the results. This study focuses on estimating four key effects: 1) the Average Treatment Effect (ATE), 2) the Marginal Treatment Effect (MTE), 3) the Treatment on the Treated (TT), and 4) the Local Average Treatment Effect (LATE), proposed by Heckman et al. (2000) and Heckman et al. (2001), and extended by Hasebe (2020), to address self-selection bias. Henceforth, these effects will be referred to by their initials. More precisely, an individual's outcome (wage) is considered with or without treatment (higher education). Thus, Y_1 is the result with treatment and Y_0 without it, so only one of these two variables is observed for each individual. To evaluate the effect of the treatment, the unobservable variable must be measured, which is obtained from the difference in means $Y_1 - Y_0$ based on the following equations:

$$D = Z\theta + U_D \tag{1}$$

$$Y_1 = X\beta_1 + U_1 \tag{2}$$

$$Y_0 = X\beta_0 + U_0 \tag{3}$$

where:

$$\begin{pmatrix} U_D \\ U_1 \\ U_0 \end{pmatrix} \sim N\left(0, \begin{bmatrix} 1 & \sigma_{1D} & \sigma_{0D} \\ \sigma_{1D} & \sigma_1^2 & \sigma_{10} \\ \sigma_{0D} & \sigma_{10} & \sigma_2^2 \end{bmatrix}\right)$$

Equation (1) stands for a latent variable of exposure to treatment. That is, it cannot be measured directly, but it allows defining a pattern of responses to a group of indicators (Willms, 2006). Since the latent variable, *D*, is found as a function of the set of independent variables contained in *Z*, then a restriction of exclusion naturally appears for the set of independent variables in *X* which determine Y_1 and Y_0.

Considering the above limitation, the selection mechanism must include at least one element in *Z* that is not found in the set *X*; see, for instance, Heckman and Vytlacil (2001). In this paper, the main selection mechanism will be the lack of access to ICT. Regarding Equations (2) and (3), Y_1 and Y_0 stand for the natural logarithm of the wage with and without the HE program, respectively. These variables, in turn, depend on a set of variables contained in *X*, determinants of the dependent variable observed in only two possible states.

Given the fact that the impact of the programs varies among individuals in the sample, certain assumptions will guide the characteristics to be evaluated. This study starts from three fundamental assumptions: 1) the effect of the program is not uniform for all individuals; 2) the effect differs between the treatment group and the control group, without being possible to anticipate the exact magnitude of such effects; and 3) even among those that decide to participate in the program, the effect may vary depending on the intensity of the observed and underlying characteristics. The latter assumption has important implications for public policy formulation since directing effectively the program towards individuals with certain characteristics can increase or decrease the impact on the target population; see, for instance, Heckman and Vytlacil (2005). To estimate private returns to education through the expected earnings in log wages, four parameters proposed by Heckman et al. (2000) and (2001) will be used. These parameters (ATE, MTE, TT, and LATE) are commonly used to evaluate program impact. Next, their interpretations and scope are briefly explained below.

ATE is defined as the expected return to the program when an individual is randomly chosen from the population that is made up of the treatment and control groups, controlling the effect on those women that do not have access to ICT. This parameter estimates the expected earnings for any person given a set of observable variables contained in $X = x$. For its estimation, the following equation is used:

$$\text{ATE}(x) = E[Y_1 - Y_0 | X = x] = x(\beta_1 - \beta_0) \quad (4)$$

This effect is useful when, instead of eliminating or reducing a program, it is necessary to expand it to the entire eligible population and make it mandatory for all people that meet certain characteristics.

The MTE parameter estimates the preferences of the individuals under study and also the expected return to the program for those individuals that are at the limit of participating, conditioned on the set of observable variables contained in $X = x$ and underlying variables contained in $U_D = u_D$. In this context, it is analyzed whether there are underlying factors that influence the decision to receive treatment and are associated with lower returns. The estimation of the parameter is formally:

$$\text{MTE}(x, u_D) = E[Y_1 - Y_0 | X = x, U_D = u_D] = x(\beta_1 - \beta_0) + (\rho_1\sigma_1 - \rho_0\sigma_0)u_D. \quad (5)$$

MTE usefulness lies in its dependence on the values of u_D, which capture the unobservable factors that affect the latent variable and that are linearly independent of the explanatory variables contained in Z. In such a way that if MTE is evaluated with high values of u_D, the average earning will be calculated for those individuals whose unobservable factors make their participation in the treatment less likely and, the opposite, for low values of u_D. If $u_D = 0$, then MTE is equal to the ATE parameter. To the extent that u_D approaches zero, it is more likely that individuals decide to carry out the program since there are no underlying factors that prevent carrying out the program.

Although MTE turns out to be the limit form of LATE, this effect is typically a useful tool to demonstrate the existence of externalities that usually affect the probability that individuals decide to take the program or not. Hence, the expected negative sign, which in the case of social programs can mean their success or failure. In the case of individuals that do not have access to ICT, it is common the presence of externalities that significantly affect the probability of participating in a HE program, and that throughout the life cycle brings negative effects related to productivity in the labor market

Regarding the TT effect, it is defined as the expected return to the program for those individuals that chose to participate and actually received the treatment voluntarily. On the other hand, the expected gain of those that have actually received the treatment ($D = 1$), subject to the set of observable variables contained in $X = x$ and $Z = z$, is given by:

$$\text{TT}(x, z, D = 1) = E[Y_1 - Y_0 | X = x, Z = z, D = 1] = x(\beta_1 - \beta_0) + (\rho_1\sigma_1 - \rho_0\sigma_0)\frac{\varphi(z\theta)}{\Phi(z\theta)} \quad (6)$$

where $\varphi(\cdot)$ stands for the density function of the standard normal random variable, $\Phi(\cdot)$ denotes its cumulative distribution function, and ρ_1 and ρ_0 are the correlation coefficients between U_1 and U_d, and U_0 and U_d, respectively. This relevance of this effect consists in demonstrating that the program registers the expected impact on the wage income of individuals that voluntarily decided to carry out the program, and that is also greater compared to those with a lower educational level.

LATE is defined as the expected return to the program due to changes in the observable factors contained in Z_k, which induce individuals to receive the program. This effect is defined from a change from $Z\theta = z\theta$ to $Z\theta = z'\theta$ having $z\theta < z'\theta$ being z' equal to z, except in the *k*-th element. To estimate this parameter, formally, it is written as:

$$\text{LATE}(D(z) = 0, D(z') = 1, X = x) = E[Y_1 - Y_0 | D(z) = 0, D(z') = 1, X = x] = x(\beta_1 - \beta_0) + (\rho_1\sigma_1 - \rho_0\sigma_0)\frac{\varphi(z'\theta) - \varphi(z\theta)}{\Phi(z'\theta) - \Phi(z\theta)}. \quad (7)$$

This effect allows simulating the program expected impacts (local effects), resulting from value variations of the variables of interest that compared directly with the results of ATE allows proposing and defining strategies that contribute to the effective achievement of the program objectives. In this study, LATE helps simulate the expected returns of individuals when parental education, household size, and the total number of individuals that do not have access to ICT vary, making it useful to estimate the impact magnitude of strategies that are of interest.

In what follows are the results obtained with the four parameters described using the two-stage process proposed above. In the first stage, a probit model is estimated with the auxiliary variable λ calculated, capturing the effect of the self-selection bias present in the latent variable *D*. In the second stage, the Mincerian wage equations are estimated, using the auxiliary variables λ, correcting the bias caused by the truncation of the variables Y_1 and Y_0 which will allow obtaining reliable parameters with emphasis on the approach to access to ICT.

4. Nature of data

To estimate the return to higher education in Mexico, information contained in the National Household Income and Expenditure Survey (ENIGH, 2020) was used. This contains information on the different socioeconomic characteristics of individuals. The most important restriction on the information available in the survey is that it does not explicitly include the socioeconomic characteristics of the family nucleus that are necessary for this study; for example, it does not include information on the latent variables that identify individuals without access to ICT, hourly wage, experience, among others, and which are important to explain the individuals' choice to adopt or not a HE program. Due to the aforementioned, it was necessary to construct the variables from the available information. The sample construction was carried out taking into account the following considerations:

a. Men and women living with their parents were included. In this way, it was possible to obtain the household head's educational level and monetary income.
b. Household heads that had a wage greater than zero were considered.
c. Salaried people that worked over 20 hours a week were considered; however, income cannot be associated with wages, for example, a scholarship was discarded.
d. The individual age was limited to 22–65 years old.

e. The proxy variable that captures individuals without access to ICT was constructed considering people that do not have internet, a computer, or a cell phone.
f. No distinction was made between individuals that graduated from public and/or private schools.
g. Non-work income was not considered, such as income from property rental, transfers, annual income for all members of the household, financial and capital earnings, income of people under 12 years of age, and any other income, since the objective is to have income only from work, allowing for homogeneous and comparable income set.

Based on the previous assumptions, a sample of 12,376 individuals was obtained using the following variables to estimate the return to the HE program:

i. Treatment: treatment variable that takes the value of 1 when the individual has a higher education program, and 0 in any other case.

For accumulated years of formal education reported, "1" was assigned to the treatment group when the number of years of education was at the following levels: Normal (16 years), Technical or Associate (15 years), Specialization (18 years), Master's and Doctor's (20 to 23 years, respectively). "0" was assigned to those individuals whose number of years of education was at the following levels: No education (0 years), Preschool (1 year), Primary (6 years), Secondary (3 years), and High School (3 years).

ii. Lwage: natural logarithm of individuals' hourly income.
iii. Household_size: number of members in the household (includes total members, guests, and domestic workers).
iv. Father_education: number of accumulated years of formal education of the household father.
v. Mother_education: number of accumulated years of formal education of the household mother.
vi. Head_wage: hourly wage of the household head.
vii. Age: individual's age at the time of the interview.
viii. Experience: number of years of work experience. Experience = Age − years of formal education − 6.
ix. Experience squared: square of the experience variable.
x. No_ICT: binary variable where 1 is without access to ICT and 0 otherwise.

Considering the above assumptions and variables, the estimates of the HE return using the four defined parameters are shown below.

5. Empirical results

According to the estimates derived from Equations (1) to (3) described in Section 3, **Figure 2** presents the sample distribution according to age groups and quintiles. The data reveals that 75.8% of individuals living with their parents are between 22 and 31 years old. Specifically, 48.4% fall within the 22 to 26 age range, and the remaining 27.4% are between 27 and 31 years old.

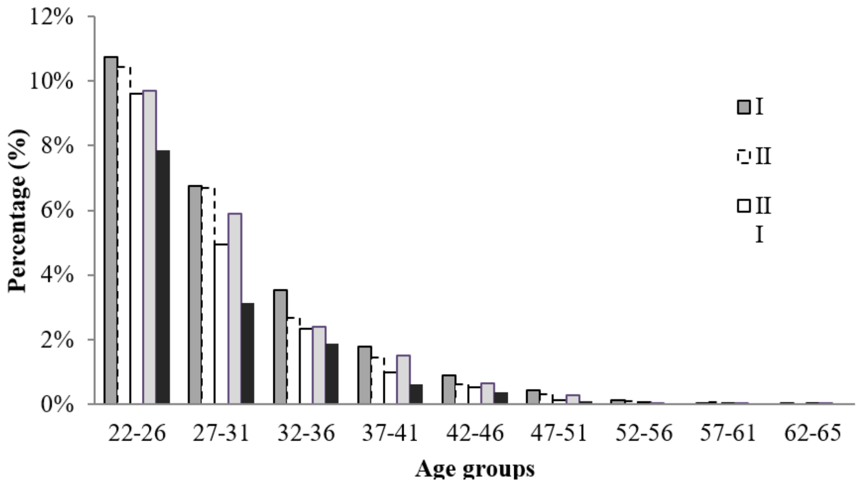

Figure 2. Distribution of individuals by age group and quintiles.

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).

Table 4. Descriptive statistics corresponding to the treatment and control groups.

Variables	Observations	Average	Standard Deviation	Minimum	Maximum
Treatment Group					
Household Size	4541	4.60	1.63	2	14
Father's education	4541	9.19	6.31	0	23
mother's education	4541	11.01	4.66	0	23
Age	4541	27.67	5.20	22	64
Experience	4541	4.11	5.06	0	40
Logarithm of wage	4541	3.44	0.96	−4.67	6.29
Without access to ICT	1922				
Women	1007				
Men	915				
With access to ICT	2619				
Women	1289				
Men	1330				
Control Group					
Household Size	7835	5.40	2.25	2	19
Father's education	7835	6.21	4.65	0	23
mother's education	7835	7.40	4.06	0	23
Age	7835	29.02	6.76	22	65
Experience	7835	12.25	7.70	3	59
Logarithm of wage	7835	2.96	0.85	−2.42	6.56
Without access to ICT	6578				
Women	2133				
Men	4445				
With access to ICT	1257				
Women	463				
Men	794				

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).

Table 4 provides descriptive statistics for the treatment and control groups. Notably, the average wage is higher in the treatment group. The treatment group also has a smaller average household size and higher parental educational levels compared to the control group. Access to ICT is a significant differentiator; 84% (6578 individuals) of the control group lacks ICT access, compared to only 42% (1922 individuals) in the treatment group. Additionally, the control group has significantly more total work experience, although the average age is similar between the groups.

Table 5 (representing the first stage of Heckman's model) shows the probit model estimation, with the dependent variable being the treatment group sample (4541 individuals) and the control group (7835 individuals). The selection variables include lack of ICT access, household head's wage, and household size.

Table 5. Probit model for the HE program.

Independent variables	**Coefficients**	***P* > |*z*|**
Constant	1.400	(0.00)*
Father's education	0.024	(0.00)*
mother's education	0.044	(0.00)*
Experience	−0.219	(0.00)*
Experience squared	0.005	(0.00)*
Head of Household Salary	0.001	(0.00)*
Household Size	−0.113	(0.00)*
Without access to ICT	−0.809	(0.00)*

Source: Own elaboration with data from the ENIGH (2020); INEGI.
a Dependent variable: Treatment (treatment and control).
* *P*(*z*) significant at 1%.

The econometric analysis indicates that the probability of participating in a higher education (HE) program increases with higher parental education and income, and decreases with larger household sizes and lack of ICT access. For work experience, the probability of participating in the HE program decreases as experience increases, but slightly increases again after a certain age.

Furthermore, when examining the variable representing work experience (measured by experience and experience squared), it was found that as experience increases over time, the probability of participating in the educational program decreases. The positive effect (second partial derivative) of experience after a certain age suggests a slight increase in the probability of adopting higher education programs. That is, after a certain age, the probability of adopting a higher education program increases marginally.

Using the probit, an auxiliary variable λ is estimated to correct for self-selection bias in the Mincerian equation. **Table 6** (the second stage of the Heckman´s model) presents the Mincerian wage equation for both treatment and control groups, showing that the variable λ is statistically significant.

Table 6. Mincerian wage equation.

Independent variables	**Coefficients**	***P* > |*t*|**
Constant	3.888	(0.00)*
Experience	0.086	(0.00)*
Experience squared	−0.002	(0.00)*
mother's education	0.011	(0.00)*
Father's education	0.006	(0.00)*
Lambda	−2.321	(0.00)*

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).
[b] Dependent variable: Lwage (natural logarithm of wage).
* *P*(*t*) significant at 1%.

Table 7 estimates wage equations for the treatment and control groups, considering the effect of self-selection bias through the auxiliary variable λ. Both estimates show that λ is statistically significant.

Table 7. Mincerian wage equation for the treatment and control groups.

Independent variables	**Coefficients**	***P* > |*t*|**
Treatment Group		
Constant	3.942	(0.00)*
Experience	0.144	(0.00)*
Experience squared	−0.004	(0.00)*
mother's education	0.002	(0.55)
Father's education	0.005	(0.03)**
Lambda	−2.303	(0.00)*
Control Group		
Constant	3.294	(0.00)*
Experience	0.048	(0.00)*
Experience squared	−0.001	(0.00)*
mother's education	0.015	(0.00)*
Father's education	0.005	(0.02)**
Lambda	−1.181	(0.00)*

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).
[c] Dependent variable: Lwage (natural logarithm of wage).
* *P*(*t*) significant at 1%.
** *P*(*t*) significant at 5%.

From the difference in means of both Mincerian equations, several parameters are estimated to evaluate the impact of the educational program: ATE, MTE, TT, and LATE. The results for these parameters are summarized in **Table 8**.

The study shows an average ATE of 7.09% for each additional year of HE for a randomly selected individual. Women have a lower average return (6.93%) compared to men (7.19%). For the treatment group (TT), the average return is 5.15%, with women again obtaining a lower return (5.13%) compared to men (5.17%). The MTE indicates that unobservable variables negatively affect the returns for those not participating in the program.

Table 8. Effects of the HE program on the wage income of individuals by gender.

Parameters	Value (%)
Average Treatment Effect (ATE)	7.09
Women	6.93
Men	7.19
Marginal Treatment Effect (MTE)	−0.14
Treatment on the Treated (TT)	5.15
Women	5.13
Men	5.17

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).

To measure the impact of ICT access on HE returns, local effects are analyzed using the ATE parameter. **Table 9** shows the expected return from marginal changes in observable variables (contained in Z_k) such as ICT access, parental education, and household size.

Table 9. Local Average Treatment Effect (LATE).

Local Average Treatment Effect (LATE)	Value (%)
Mother's education	7.15
Father's education	7.12
Household Size	6.92
Without access to ICT	5.91
Women	5.85
Men	6.00

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).

Given a marginal increase in the number of individuals without access to ICT, the return on HE decreases by 1.18 percentage points, dropping from 7.09% in the Average Treatment Effect (ATE) to 5.91% in the Local Average Treatment Effect (LATE). This reduction is more pronounced when disaggregated by gender: for women, the effect decreases from 6.93% in ATE to 5.85% in LATE, representing a decline of 1.08 percentage points; for men, the effect falls from 7.19% in ATE to 6.00% in LATE, a reduction of 1.19 percentage points.

Moreover, an increase in a mother's education marginally raises the likelihood of her sons and daughters participating in the HE programs, subsequently increasing their wage income by 0.06 percentage points, from 7.09% in ATE to 7.15% in LATE. Similarly, an additional year of a father's education results in a positive marginal return to the program, enhancing the wage income of their sons and daughters by 0.03 percentage points, from 7.09% in ATE to 7.12% in LATE.

The impact of "Household Size" also warrants attention. A marginal increase in household size reduces HE returns by 0.17 percentage points, lowering the effect from 7.09% in ATE to 6.92% in LATE.

Finally, to ensure the reliability of these findings, robustness tests assessing both internal and external validity are provided in the Appendix.

6. General discussion

It is worth noting that the ATE parameter, representing the expected wage gain per additional year of HE for a randomly selected individual from the sample, was 7.09%. This positive value indicates that individuals who pursued HE experienced higher salary returns compared to those with less education. Given Mexico's persistent gender wage gaps, distinguishing this impact by gender confirmed inequality, with women obtaining an average return of 6.93%, while men achieved an average return of 7.19%. This evidence is crucial for policymakers aiming to effectively target wage policies.

The MTE parameter, with a negative value of −0.14%, indicates that unobservable factors (externalities) reduce the likelihood of individuals with generally lower wage returns participating in HE programs. For those lacking ICT access, externalities such as labor market barriers, economic constraints, and inadequate local infrastructure contribute to accumulating negative effects throughout their lifecycle, impacting early learning and long-term outcomes.

The TT parameter was positive (5.15%), though lower than the ATE, indicating that the HE programs had a positive effect on the wages of individuals who voluntarily participated, compared to those with less education. Gender-distinguished impacts again highlighted inequality, with women obtaining an average return of 5.13% and men 5.17%.

To measure the impact of ICT access on education returns, the LATE parameter was employed. This tool's flexibility allowed for simulating the effects of marginal changes in specific variables, compared with the ATE, suggesting that lack of ICT access significantly diminishes HE returns, resulting in lower economic well-being due to reduced wage income. Overall, the absence of ICT access led to returns dropping from 7.09% to 5.91%. Gender-distinguished impacts showed returns of 5.85% for women and 6.00% for men.

In summary, these findings underscore the importance of addressing ICT access in education policies to mitigate income inequality and improve economic outcomes for all people, regardless of gender.

7. Conclusions

The primary objective of this study has been to assess the impact of access to ICT on the private return to HE in Mexico focusing on income inequality. This study utilized data from the National Household Income and Expenditure Survey (ENIGH) 2020 to construct a sample to evaluate how ICT access influences HE wage returns in Mexico with a gender perspective

A Heckit model was employed to estimate four key effects of interest, accounting for persistent heterogeneity between the treatment and control groups, as well as sample self-selection bias. The constructed sample included socioeconomic and occupational characteristics of individuals still residing with their parents, providing insights into how social and familiar environments impact educational attainment and wage returns of HE, with a particular emphasis on ICT access.

The empirical results suggested significant differences between the study groups. Those with access to an HE program showed a positive and greater impact on their income compared to those with lower educational levels and no ICT access. Women without ICT access had the lowest wage returns, emphasizing the gender disparities in HE returns.

This research highlights the priority of reducing barriers to access to higher education and expanding higher education programs to a broader population through gender-focused public policies, which could positively affect the social and family environments. This would allow men and women to access higher salary income, improving their general well-being. Public policies must also prioritize the incorporation of more women into universities, promote the strengthening of educational systems and build a better educational and technological infrastructure to reduce the existing economic and social inequalities. Finally, access to ICT should be considered as one of the criteria that integrate social deprivation in the measurement of multidimensional poverty.

This investigation had certain limitations, such as not distinguishing between graduates of public and private schools or considering non-wage income sources. Additionally, the use of ENIGH 2020 data may limit the generalization of the results to other contexts not covered by the survey. In this sense, this research was carried out with data of 2020, when the COVID-19 pandemic occurred. During that time, the public and private sectors were required to work online and the results obtained in this research may not be valid in the post-COVID-19 era.

Finally, for future research, it is intended to explore the role of other factors, such as socioeconomic level, geographic location, educational policies and post-COVID-19 era in HE returns with a gender focus. It would also be relevant to investigate how specific ICT training programs for women could reduce wage disparities and promote labor inclusion. Longitudinal studies could analyze the evolution of educational and work returns over time.

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Appendix

To show the robustness (internal and external validity) of the results obtained, the performance of the HE on the income of individuals from a subsample that does not consider women is shown below in **Tables A1** and **A2**.

Table A1. Effects of the ES program on the wage income of individuals.

Parameters	**Value (%)**
Average Treatment Effect (ATE)	5.12
Marginal Treatment Effect (MTE)	−0.53
Treatment on the Treated (TT)	0.77

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).

Table A2. Average local effect of HE treatment.

Local Average Treatment Effect (LATE)	**Value (%)**
Mother's education	5.44
Father's education	5.28
Home size	4.26
Without ICT	0.15

Source: Own elaboration with data from the ENIGH (2020); INEGI (2020).

The results reveal sufficient evidence to show that when a smaller sample is used, the private returns of the HE tend to be lower, which suggests that to the extent that the sample used is larger it will also be possible to find higher returns without changing the meaning of the previously demonstrated results. The main implication of having compared the two samples is that the methodology used and the results obtained could be generalized based on the estimated parameters of interest (ATE, MTE, TT and LATE), which differed only in magnitude derived from the size of the samples, but not in the implications demonstrated in the economic literature in this type of studies.