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Technological change and income inequality in Mexico

Cambio tecnológico y desigualdad de ingresos en México

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Abstract

The objective of the work is to analyze income inequality in Mexico during the third quarter of 2018 and 2021 with information from the National Survey of Occupation and Employment (ENOE) of the National Institute of Statistics and Geography (INEGI). The link between workers' earnings and a technology variable, constructed from the automation probabilities estimated by Frey and Osborne (2017), is examined. Control variables such as gender, schooling, type of employment, regional and sectoral structure of the Mexican economy are considered. A procedure is implemented to correct the sample self-selection bias problem. Estimates indicate that those who perform occupations with a medium and high level of automation earn less than those with a low level of automation. During 2018 the percentages were minus 25% and 30% and during 2021, minus 23% and 28% respectively.

JEL Code: J01, J08, J31
Keywords: income inequality; technological change; Heckman correction

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Resumen

El objetivo del trabajo es analizar la desigualdad de ingresos en México durante el tercer trimestre de 2018 y 2021 con información de la Encuesta Nacional de Ocupación y Empleo (ENOE) del Instituto Nacional de Estadística y Geografía (INEGI). Se examina el vínculo entre los ingresos de los trabajadores y una variable de tecnología, construida a partir de las probabilidades de automatización que estiman Frey y Osborne (2017). Se consideran variables de control como el sexo, escolaridad, tipo de empleo, estructura regional y sectorial de la economía mexicana. Se instrumenta un procedimiento para corregir el problema de sesgo por autoselección muestral. Las estimaciones indican que quienes desempeñan ocupaciones con nivel medio y alto de automatización, ganan menos con respecto a quienes exhiben un bajo nivel de automatización. Durante 2018 los porcentajes fueron de menos 25% y 30% y durante 2021, de menos 23% y 28% respectivamente.

Código JEL: J01, J08, J31
Palabras clave: desigualdad de ingresos; cambio tecnológico; corrección de Heckman

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Introduction

The effect of technology on the evolution of the labor market is a topic of debate and reflection addressed in academic circles and the business and public sectors. Understanding the process of technological change and its effects on the economy is a notable line of study for science and for those who implement public policies. Interest is focused on analyzing the link between technological change and income inequality. Although other aspects could be explored in labor economics, it is also stated that the income gap can reduce the quality of life of less skilled workers.

The literature suggests that introducing new technologies in production processes leads to a greater demand for skilled labor and a contraction of the labor force with fewer qualifications and skills. One implication of the changes in the relative demand for labor is that they can trigger income inequality among different segments of the labor force. Therefore, it is important to emphasize that the effects of this phenomenon may vary from country to country, between sectors and regions and localities, due to the heterogeneity of labor. The relation between technological change and inequality is not an isolated issue; on the contrary, it is a phenomenon that has been attracting the attention of various multilateral institutions such as the International Labor Organization (ILO), the Economic Commission for Latin America and the Caribbean (ECLAC) and the Organization for Economic Cooperation and Development (OECD).

One particularity of the empirical studies that address the object of study is that they use data structures and estimation methodologies that vary according to the time and spatial horizon of the information. The findings have allowed a deeper understanding of the phenomenon and laid the groundwork for further exploration of other topics of technological change and the labor market. One characteristic of those studies that are part of the specialized literature is related to how a variable that approximates technological change is constructed and how the control variables are specified in the econometric models. There is a clear idea that income inequality is closely related to incorporating technology into economic activity. Since occupations are exposed to a certain degree of technological intensity, it is foreseeable that they will impact the dynamics of employment and unemployment, both on an aggregate scale and by region, size of establishment, and productive sector. Accordingly, it is desirable to estimate the magnitude of the effect of technological change on labor income and, thus, to provide guidelines that can orient the implementation of public policies.

The research aims to analyze the relation between a technological intensity variable associated with occupations and workers' income in Mexico during the third quarters of 2018 and 2021. Microdata from the National Occupation and Employment Survey (ENOE; Spanish: Encuesta Nacional de Ocupación y Empleo) are used and income functions are estimated with cross-sectional data. The two-stage Heckman method is used to correct for a possible self-selection problem. The technology variable is constructed from Frey and Osborne's (2017) estimated automation probabilities. The target variable is the monthly income of employed personnel aged 16-65. The control variables are gender, branch of economic activity, age range, school grades, region, type of formal/informal occupation, and rural-urban setting. It is proposed that technological change measured by the probabilities of automation of occupations contributes to explaining the inequality between workers with different levels of competence and qualifications.

It is argued that those workers who perform tasks with a lower level of automation are less likely to be replaced by technology since they perform more specialized and abstract tasks. The paper is divided into four sections that complement this introduction. In the first section, a review of the theoretical and empirical literature on the object of study is carried out, discussing and contrasting the main findings. In the second part, the variables and sources of information are described, and a preliminary exploratory analysis is carried out. The third section develops the econometric methodology and states the estimation results of the econometric model. Finally, general conclusions are drawn based on the empirical work, and some public policy guidelines are proposed within the framework of the econometric results.

Technology and income inequality; Literature review

The idea that technological change has been biased in favor of skills and that education and technology are related to the wage structure was addressed by Tinberger (1974). During the 1990s and the beginning of the new millennium, numerous authors began to study the role of technical change in income inequality, with contributions by Atkinson (2008), Acemoglu (2002), and Katz and Murphy (1992) standing out. Under the Hypothesis of Biased Technological Change (HBTC) associated with Acemoglu, a framework that links wages to the supply of skills is delineated. Two types of workers are conceived, skilled and unskilled, who, in turn, are imperfect substitutes. Acemoglu points out that less skilled workers have a high school diploma or certificate, while skilled workers have a bachelor's or higher degree. The HBTC has been questioned by Card and DiNardo (2002), who argue that wage inequality did not continue to increase during the 1990s despite accelerated technological development. Meanwhile, Atkinson (2008) considers other elements that are not taken into account, such as the interaction between education, technology, and capital markets.

Acemoglu and Autor (2010) highlight the virtues of the canonical model of labor supply and demand but also note shortcomings of the classical model, such as the fact that it does not allude to the tasks related to occupations. Conversely, the task approach posits that the analysis of technology in relation to employment requires differentiating work not by its level of qualification or skills but by the set of tasks performed (Apella & Zunino, 2017). A task is an activity that enables the production of a product, and skills can be viewed as the ability of workers to perform specific tasks. Tasks can be classified as routine and non-routine. Routine tasks involve a clear and repeated set of actions that do not change and are susceptible to computerization. A non-routine task involves different actions that change continuously and require adaptation to the context.

According to Apella and Zunino (2017), tasks in each of the categories of routine and non-routine can be manual or cognitive, i.e., they relate to physical or knowledge work. One of the most relevant research papers considering occupations is Frey and Osborne (2017); they ask how susceptible jobs are to computerization. In this approach, they state that tasks are at risk rather than jobs, as there are tasks that are likely to be displaced by new technologies. Lemieux (2006) had already identified that a large proportion of the growth in residual inequality between 1973-2003 was due to compositional effects, especially the increase in experience and schooling, which are two factors associated with a large intra-group wage dispersion, i.e., between workers with the same level of schooling or experience. Meanwhile, Autor, Katz, and Kearney (2008) recognized that both the growth in the demand for workers with higher levels of education and wage inequality in the United States slowed down in the 1980s, finding evidence of a polarization in the wage distribution.

By extending the decomposition technique of Machado and Mata (2005), Autor et al. (2008) observe that contrary to what Lemieux (2006) predicted, changes in the composition of the labor force only affected the lower part of the distribution. However, changes in inequality between groups explain the large increase in inequality in the upper part of the distribution. The task approach shows that technological changes do not increase the demand for the most skilled workers. Author Levy and Murnane (2003) proposed distinguishing tasks according to how routine they are, i.e., information technologies are substitutes for labor in routine tasks but complement human capital in non-routine tasks. New technologies can be complementary and substitutes since they complement highly skilled workers performing abstract tasks but can substitute for middle-skilled workers performing routine tasks.

For Ghiara and Zepeda (2004), what happens with employment and wage differences in Mexico can be explained with the model of technological change biased by qualification against the Stolper-Samuelson theorem, which is based on the Heckscher Ohlin model, which fails to explain the wage differences of workers. In their paper, Camberos, Huesca, and Castro (2013) test the biased technological change hypothesis using computer equipment as an indicator. They find evidence of increases in wage inequality caused by technological change in the service sector. More recently, Nigenda and Teshima (2017) concluded that the estimation of models assessing the effect of technological change on wage inequality in Mexico should go beyond traditional skill measures, and the task approach should be incorporated into the analysis.

Calderon, Hernandez, and Ochoa (2018) analyze wage inequality in the manufacturing industry on the northern border of Mexico and the southern United States during 1994-2014. Using a Gini coefficient decomposition that is based on cooperative game theory and with data from the National Urban Employment Survey (ENEU; Spanish: Encuesta Nacional de Empleo Urbano) for 1994 and the ENOE for 2014, as well as the Currency Population Survey (CPS) for the United States, they find that while average wages in the southern states of the United States tended to increase, in Mexico they fell by more than 100%. On the other hand, Rodriguez and Castro (2012) reviewed the regions of Mexico from 2000-2008. They found increased wage differences between workers in technological and non-technological jobs, highlighting that the largest differences were found between regions.

Through dynamic panel data models, Tenorio and Sanchez (2013) show the existence of the schooling premium hypothesis and its relation with the relative supply of skilled labor in the case of Mexico. Felix and Torres (2016) review whether compensation differences depend on whether workers use computers. With information from the ENOE and the National Survey on the Availability and Use of Information Technologies in Households (ENDUTIH; Spanish: Encuesta Nacional sobre Disponibilidad y Uso de Tecnologías de la Información en los Hogares), they find that the mean compensation of those who use a computer is higher than the mean of those who do not.

Vera and Galassi (2010) investigated the heterogeneity in the empirical relation between income and schooling in Argentina and Mexico in 2008. They use data from the Permanent Household Survey (EPH; Spanish: Encuesta Permanente de Hogares) of Argentina and the National Household Income and Expenditure Survey (ENIGH; Spanish: Encuesta Nacional de Ingresos y Gastos de los Hogares) of Mexico. Mincer-type quantile and Ordinary Least Squares regressions are estimated for both countries. The results show that in Argentina, there are no differences between the OLS and quantile regression results. For Mexico, the differences are considerable. In both countries, the gender variable has a differential impact on income, with Argentina having a larger gender gap than Mexico.

Using data from the National Urban Employment Survey for 1988-1999, Meza (2005) shows an increasing trend in wage inequality in Mexico. Panel data are used to estimate a relative wage model and analyze wage inequality between two types of workers. The estimates suggest that the increase in the supply of workers with higher education reduces wage inequality in the middle part of the distribution. Nigenda and Teshima (2017) use the urban labor force survey and employ a model based on Firpo et al. (2009), which estimates quantile regressions. They conclude that incorporating occupational task content can enrich understanding wage inequality in developing countries.

According to the report conducted by the McKinsey Global Institute (Manyika et al., 2013), the benefits of technologies may not be evenly distributed. Although each new technology can potentially create significant value, in some cases, this value will not be distributed evenly. It may even contribute to increasing income inequality. The advance of technology, the automation of knowledge in jobs, or advanced robotics may create disproportionate opportunities for some highly skilled workers and owners of capital while replacing the work of some less skilled workers with machines.

Sources of information and variables description

The data used in the estimations were obtained from the ENOE microdata module generated by INEGI (Spanish: Instituto Nacional de Estadística, Geografía e Informática). The variable of interest is hourly earnings. For the third quarter of 2018, 147 718 observations are considered, and for the same quarter of 2021, 155 705 data. For the first year, 66.89% of the employed personnel reported a non-zero income, and for the second period, 67.37%. In order to avoid the problem of self-selection bias, the two-stage methodology of Heckman (1979) is used.

Table 1 shows the percentage distribution of the variables involved in the estimates. Regarding the age variable, it is observed that employed personnel in the ranges of 16 to 19 and 60 to 65 years old are less represented; the first interval represents 5.52% and the second 5.01% of the total. The population from 30 to 39 years old predominates, representing 24.51% in 2018 and 24.33% in 2021. Regarding the educational level, it is observed that the population with a high school diploma, degree from a teacher-training college, and technical and professional careers is higher in both years. The labor force with master's and doctorate degrees has less weight. Nevertheless, it can be noted that it went from 2.2% to 2.4% from one year-quarter to the other. The Central and Northern regions have the largest employed population, though there was a notable decrease from one year to the next. In the context of the crisis, this population segment, which can be considered highly qualified, declined.

The sectors of economic activity with the highest concentration of employed personnel are commerce, services, and the manufacturing industry; the agricultural sector is one of the sectors with the smallest labor force. The participation of men in the labor market is higher than the participation rate of women. Although formal employment predominates, it is also observed that the number of people working informally is very high, which reveals a duality in the labor market of the Mexican economy. The technology variable is approximated from a low, medium and high level of automation of occupations. Low-level activities are those with a probability equal to or less than 0.3, medium-level activities range between 0.31 and 0.69, and occupations with a high level of automation have probabilities equal to or greater than 0.7. This classification is supported by the methodology of Frey and Osborne (2017).

Table 1
Frequencies and percentages of variables for the third quarters of 2018 and 2021

	2018			2021		
Variable	Frequency	Percentage	Accumulated	Frequency	Percentage	Accumulated
Age						
16-19	8 156	5.52	5.52	8 369	5.37	5.37
20-29	36 110	24.45	29.97	36 934	23.72	29.1
30-39	36 209	24.51	54.48	37 876	24.33	53.42
40-49	35 060	23.73	78.21	36 628	23.52	76.94
50-59	24 776	16.77	94.99	27 430	17.62	94.56
60-65	7 407	5.01	100	8 468	5.44	100
Educational level						
Up to elementary school	28 643	19.39	19.39	26 314	16.9	16.9
Secondary	43 040	29.14	48.53	44 001	28.26	45.16
High School	33 174	22.46	70.98	38 127	24.49	69.65
Vocational, technical, and professional careers	39 613	26.82	97.8	43 502	27.94	97.58
Master’s and doctorate degrees	3 248	2.2	100	3 761	2.42	100
Automation						
low	29 292	19.83	19.83	30 769	19.76	19.76
medium	32 219	21.81	41.64	32 595	20.93	40.69
high	86 207	58.36	100	92 341	59.31	100
Regions						
Northern border	29 500	19.97	19.97	34 583	22.21	22.21
North	30 993	20.98	40.95	30 490	19.58	41.79
Center	46 674	31.6	72.55	48 011	30.83	72.63
Capital	10 481	7.1	79.64	9 785	6.28	78.91
South	13 498	9.14	88.78	15 572	10	88.91
Yucatan Peninsula	16 572	11.22	100	17 264	11.09	100
Economic activity sector						
Construction	13 520	9.15	9.15	13 795	8.86	8.86
Manufacturing industry	25 875	17.52	26.67	28 493	18.3	27.16
Trade	26 634	18.03	44.7	29 007	18.63	45.79
Services	69 634	47.14	91.84	71 176	45.71	91.5

Others	1 350	0.91	92.75	1 407	0.9	92.4
Agricultural	9 951	6.74	99.49	10 783	6.93	99.33
Not specified	754	0.51	100	1 044	0.67	100
Gender						
Male	88 980	60.24	60.24	93 465	60.03	60.03
Female	58 738	39.76	100	62 240	39.97	100
Type of employment						
Informal employment	73 323	49.64	49.64	77 300	49.65	49.65
Formal employment	74 395	50.36	100	78 405	50.35	100
Urban/Rural						
Urban	93 983	63.62	63.62	102 513	65.84	65.84
Rural	53 735	36.38	100	53 192	34.16	100

Source: created by the authors with data from ENOE (INEGI)

This study considered the regions proposed in Hanson (2003), which are six: Northern Border (Baja California, Chihuahua, Coahuila, Nuevo León, Sonora, and Tamaulipas), North (Aguascalientes, Baja California Sur, Durango, Nayarit, San Luis Potosí, Sinaloa, and Zacatecas), Center (Colima, Guanajuato, Hidalgo, Jalisco, Michoacán, Morelos, Puebla, Querétaro, Tlaxcala, and Veracruz), Capital (Mexico City and the State of Mexico), South (Chiapas, Guerrero, and Oaxaca), and Yucatán Peninsula (Campeche, Tabasco, Quintana Roo and Yucatán).

Several empirical studies that have addressed the subject of study for Mexico have used information from the Mexican Classification of Occupations (CMO; Spanish: Clasificación Mexicana de Ocupaciones). INEGI (2011) points out that in Mexico, there are two different instruments for classifying occupations: the National Occupations Catalog (CON; Spanish: Catálogo Nacional de Ocupaciones) published by the Ministry of Labor and Social Welfare (STPS; Spanish: Secretaría del Trabajo y Previsión Social) in 2000 and the CMO. The two instruments pursue different, although complementary, objectives since one focuses on labor linkage and certification of competencies and the other on generating statistical information on labor occupations.

According to INEGI, the CMO has restrictions for ordering occupations based on competencies and making international comparisons. In this paper, the CON and CMO are considered together with the International Standard Classification of Occupations (CIUO; Spanish: Clasificación Internacional Uniforme de Ocupaciones) of the ILO. The purpose is to have a standardized National Occupational Classification System (SINCO; Spanish: Sistema Nacional de Clasificación de Ocupaciones), which reflects the occupational structure of the country with a vision of the future and can be compared with other international classification systems, mainly with that of the ILO and Mexico's main trading partners (United States of America and Canada). The SINCO is ordered by occupations, defined as "the set of tasks and duties performed by a person, or expected to be performed by a person, including for an employer or on one's account" (INEGI, 2011). It is a system that orders occupations by level of competence, and occupational categories are classified into 9 divisions (see Table 2).

Table 2
SINCO occupational categories and competency level, 2011

Proficiency Level		Occupational Categories
3 and 4 (High)	1.	Officers, directors, and managers
	2.	Professionals and technicians
2 (Medium)	3.	Auxiliary workers in administrative activities
	4.	Retailers, sales clerks, and sales agents
	5.	Personal and security services workers
	6.	Workers in agriculture, livestock, forestry, hunting, and fishing
	7.	Craft workers
	8.	Industrial machinery operators, assemblers, chauffeurs, and transport drivers
1 (Low)	9.	Workers in basic and support activities

Source: INEGI (2011)

In this paper SINCO is used to generate a proxy variable for technology based on the probabilities of automation of occupations estimated by Frey and Osborne (2017). It should be noted that these estimates have already been considered in other empirical papers, such as Minian and Martinez (2018), where the advance of technology is analyzed but fundamentally linked to employment in Mexico. Probabilities close to 1 are associated with occupations with a high degree of automation and close to 0 with a low degree of automation. Frey and Osborne developed an algorithm and predicted the probability of automation for 702 occupations of the Standard Occupational Classification system (COU; Spanish: Clasificación Ocupacional Uniforme). An advantage of this system is that occupations may be matched with INEGI's SINCO. Table 3 illustrates a partial example of how keys were used to match the SINCO and COU to assign the estimated probabilities that allow occupations to be classified by level of automation. This comparative process also used the COU manual (BLS, 2010).

Automation probabilities are based on criteria directly related to technology and the degree of substitution of occupations. Occupations with a low level of automation (low probability of automation) are highly skilled; it is more difficult for them to be substituted by technology since they perform more abstract tasks complemented by technology. According to the HBTC, their wages would increase over time, while lower-skilled workers would decrease in relative terms, leading to income inequality. It is argued that the probabilities of automation do not change in the short run but over the long run. This is how they reflect the estimates for 2018 and 2021. As already specified, the research follows in the wake of other empirical works where the Frey and Osborne (2017) approach has also been used. The particularity of this paper is that estimates of extended income functions are made where occupations are related to technology through their degree of automation. Two related papers are Minian and Martinez (2018) for Mexico and Domenech, Garcia, Montañez, and Neuta (2018) for Spain.

Table 3
Assignation of automation probabilities for Mexico*

INEGI comparative tables					Frey and Osborne (2013)	
SINCO	Occupation (4 digits)	Prob. SINCO	COU	Occupation (5 digits)	Automation probability	COU (6 digits)
2413	Dentists	0.0044	29-1020	Dentists	0.0044	29-1021 (Dentists)
8111	Machinery and equipment operators for extraction and beneficiation in mines and quarries	0.5683	47-5040	Mining machinery operators	0.54 and 0.59	47-5041 (Continuous mining machine operator) and 47-5042 (Mine cutting and channeling machine operators)
			53-7040	Hoist and winch operators	0.65	53-7041 (Hoist and winch operators)
			47-5060	Roof bolters, mining	0.49	47-5061 (Roof bolters, mining)
8114	Specialized portable construction equipment operators	0.8667	47-2070	Construction equipment operators	0.82, 0.83 and 0.95	47-2072 (Pile driver operators), 47-2071 (Paving, surfacing, and tamping equipment operators), and 47-2073 (Operating engineers and other construction equipment operators)

Source: created by the authors
*Three occupations (2413, 8111, and 8114) are illustrated as examples of the procedure performed for 401 occupations in SINCO

Once the level of automation of occupations in Mexico has been calculated, it is possible to compare the two years of study. In Figure 1, the percentage of employment with a low level of automation remains stable between 2018 and 2021, representing 19.83% and 19.76%, respectively. In the case of medium-level occupations, a decrease from 21.81% to 20.93% is observed. The percentage of jobs with a high level of automation increased slightly from 58.36% to 59.31%. The percentage of jobs with a high level of automation predominates in the Mexican economy, which is associated with automation probabilities equal to or greater than 0.7; it is work that can be replaced by technology and is characterized by a lower level of competition and salary.

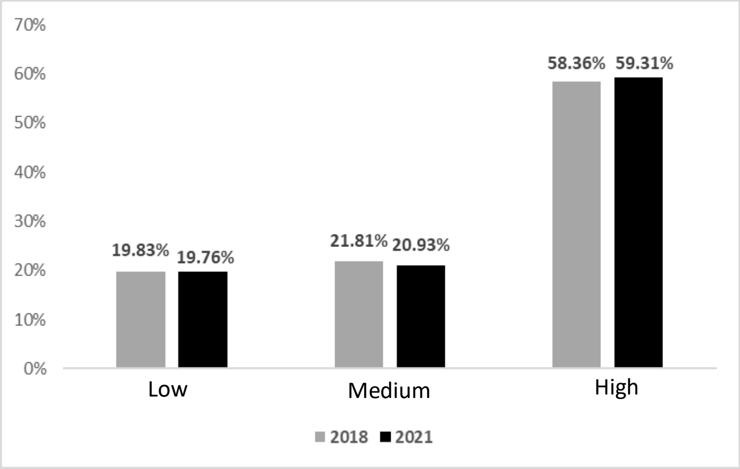

Figure 1. Percentage of jobs by level of automation 2018-T3 and 2021-T3*
Source: created by the authors with data from ENOE, COU, and Frey and Osborne (2017)
*The ranking of automation levels was taken from Frey and Osborne (2017) with data on automation probabilities for 401 occupations in Mexico

The data in Table 4 enables different levels of automation to be compared with different minimum wage ranges. In 2018, the number of employed persons who register a high level of automation is closely related to the population earning up to one minimum wage, more than one and up to two, more than two, and up to three. On the other hand, most of the employed who report an income equivalent to more than three minimum wages and up to five also exhibit a high level of automation. Nevertheless, they represent a smaller number than previous wage intervals. These figures reveal that workers earning lower wages are more susceptible to being replaced by the development of technology. These population segments could perform more routine tasks that demand less specialization in production processes. In the first four intervals of the distribution, there is a remarkable gap between those with a low and medium level of automation and those with a high level of automation. In the case of the employed who earn over five minimum wages, it is identified that the gap is inverted. Most of the employed show a low level of automation, referring to a more specialized workforce that may be less affected by technological change. Among the total employed population registered in 2018, 147 718 workers, only 8 075 reported earning more than 5 minimum wages; within these, 4 192 registered a low level of automation, 1 982 a medium level, and only 1 901 a higher level. It is noted that the 4 192 employed are the group of workers earning more than five minimum wages, but also the one that can be least affected by the process of technological change.

In 2021, practically the same pattern is reproduced, but with some variations. For example, an increase is observed in jobs with high levels of automation that receive up to one minimum wage and from

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more than one up to two. In the case of those earning more than two minimum wages up to three and also showing a high level of automation, the figure decreases compared to 2018. In the case of the segment earning more than three minimum wages and up to five, it can be seen that the number of employees with a low level of automation is higher than that reporting a high level. This result contrasts with what was observed for 2018, specifically in that interval. As in 2018, in 2021 the gap between the number of employed people earning over five minimum wages reporting a low and high level of automation is very sharp. Although in both years the total numbers of employed individuals and wages differ, it is noteworthy that the workforce with the lowest level of automation is the one that earns the highest income.

Table 4
Employed population by income level and Automation 2018 and 2021 (thousands employed)

Classification of the employed population by income level	Automation level							
	2018				2021			
	Low	Medium	High	Total	Low	Medium	High	Total
Up to one minimum wage	2 274	4 481	10 887	17 642	4 659	7 503	20 700	32 862
More than 1 up to 2 minimum wages	4 047	8 670	28 214	40 931	7 498	12 031	38 674	58 203
More than 2 up to 3 minimum wages	4 301	6 439	18 363	29 103	6 251	4 973	11 427	22 651
More than 3 up to 5 minimum wages	7 302	5 443	9 710	22 455	4 424	2 657	4 081	11 162
Over 5 minimum wages	4 192	1 982	1 901	8 075	2 021	917	1 154	4 092
No income received	177	205	6 643	7 025	205	227	6 495	6 927
Not specified	6 999	4 999	10 489	22 487	5 711	4 287	9 810	19 808
Total	29 292	32 219	86 207	147 718	30 769	32 595	92 341	155 705

Source: created by the authors with data from ENOE-INEGI

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Methodology and discussion of results

Considering the characteristics of the database and the fact that some individuals do not report information on their income, the two-stage Heckman methodology was implemented to solve a possible problem of self-selection bias. The procedure consists of estimating a decision equation based on the full sample. Subsequently, the equation of interest is estimated, trying to obtain consistent and asymptotically normal estimators. The decision equation is a specification that captures the participation of individuals in the labor market and is defined as a bivariate probit model:

$$P\left(s = \frac{1}{z}\right) = \Theta(z\gamma) \tag{1}$$

$$s = 1[z_0 + z_1\gamma_1 + z_2\gamma_2 + \cdots + z_m\gamma_m + \nu \geq 0] \tag{2}$$

Where s=1 if the logarithm of income is observed and zero otherwise. In Equation 1, z variables are included. Wooldridge (2010) outlines that x must be a strict subset of z for the estimation method to work correctly, but, in addition, it is feasible for some variables included in z also to be part of x. Once the first stage has been carried out, consistent with the estimation of Equation 1, in the following stage the equation of interest is estimated, which is a semi-logarithmic model that seeks to explain the income of individuals based on economic, regional, and socio-demographic indicators, including a critical explanatory variable, which is the automation of occupations. The equation of interest is formally specified as:

$$E\left(\frac{y}{z}, s = 1\right) = x\beta + \rho\lambda(z\gamma) \tag{3}$$

The expected value of y given z is equal to xβ, plus an additional term that depends on the Mills ratio evaluated at zγ. The inverse of the Mills ratio for each i is expressed as:

$$\lambda = \lambda(z_i\gamma) \tag{4}$$

The variable used in the decision Equation 1 that is not part of the income equation or of interest [3] is household size. The variables that are part of x are age range, level of schooling, economic region, sector of economic activity, gender, type of occupation, type of locality (rural/urban), formality of employment, and a categorical variable that expresses the level of automation of the occupations. The explanatory variables of gender, formality of employment, and locality are dichotomous, while the rest, having more than two categories, are incorporated into the model through a vector that considers m-1 dichotomous variables to avoid the problem of perfect multicollinearity.

The regression results for the third quarter of 2018 and 2021 are reported in Table 5. Estimates are illustrated by the conventional Ordinary Least Squares OLS method and the two-stage Heckman procedure. The Maximum Likelihood (ML) procedure estimates the decision equation or probit model. All explanatory variables are relevant at standard confidence levels, and the coefficients' signs are practically preserved for all variables in both years. The Mills Lambda coefficient in the income equation is statistically significant, suggesting that the results have been adequately corrected. The goodness of fit in both models is reasonably acceptable with multiple coefficients of determination of around 0.28 and p-values of the F-statistic less than 0.05. Considering that the OLS estimates are affected by self-selection bias, the analysis of results concentrates specifically on the corrected estimates reported in the column referring to Heckman. It is important to note that when contrasting the uncorrected and corrected coefficients, there is evidence of under/overestimation in the OLS estimators.

Table 5
OLS and Heckman regressions for 2018 and 2021

	2018-T3			2021-T3		
Variable	OLS	Two-stage method		OLS	Two-stage method	
Age		Heckman	Probit		Heckman	Probit
16-19 (reference)						
20-29	.0821***	.0981***	-.2079***	.0910***	.1009***	-.1812***
30-39	.1845***	.2052***	-.2565***	.1893***	.2074***	-.2738***
40-49	.2030***	.2326***	-.3444***	.2144***	.2361***	-.3435***
50-59	.1749***	.2059***	-.3710***	.2014***	.2265***	-.3942***
60-65	.1524***	.1861***	-.4140***	.1553***	.1841***	-.4571***
Schooling						
Up to elementary (reference)						
Secondary	.0792***	.0876***	-.0849***	.0742***	.0780***	-.0488***
High School	.1667***	.1901***	-.2377***	.1597***	.1741***	-.2152***
Vocational, technical, and professional careers	.4260***	.4805***	-.4954***	4082***	.4393***	-.4252***
Master's and doctorate degrees	.8921***	.9634***	-.6090***	.8409***	.8789***	-.4804***
Automation level (fosinco)						
Low (reference)						
medium	-.2310***	-.2559***	.1999***	-0.2237***	-.2396***	.1828***
high	-.2810***	-.3040***	.1832***	-0.2676***	-.2805***	.1603***
Regions-Hanson						

Northern border (reference)						
North	-.0964***	-.1043***	.0864***	-0.0687***	-.0633***	-.0448***
Center	-.1497***	-.1336***	-.1242***	-0.1704***	-.1439***	-.3364***
Capital	-.1792***	-.0934***	-.6343***	-0.2035***	-.1355***	-.7427***
South	-.3697***	-.3806***	.1143***	-0.3993***	-.3872***	-.0952***
Yucatan Peninsula	-.2117***	-.2455***	.3493***	-0.1893***	-.1941***	.0756***
Economic activity sector (Branch)						
Construction (reference)						
Manufacturing industry	-.2182***	-.2067***	-.1268***	-0.2068***	-.2026***	-.0559***
Trade	-.4042***	-.3893***	-.1639***	-0.3998***	-.3942***	-.0713***
Services	-.0959***	-.0732***	-.2324***	-0.0764***	-.0660***	-.1440***
Others	.1110***	.1371***	-.2747***	.1108***	.1309***	-.2873***
Agricultural	-.4507***	-.3919***	-.5679***	-0.4258***	-.4038***	-.3390***
Not specified	-.2441***	-0.0722	-1.3504***	-0.0873**	0.0296	-1.332***
Gender (sex)						
Male(reference)						
Female	-.1074***	-.1179***	.0929***	-0.0945***	-.1019***	.0888***
Occupation type						
Subordinate and paid workers(reference)						
Employers	.2957***	.3288***	-.2774***	.3314***	.3511***	-.2471***
Self-employed workers	.0175**	.0544***	-.3356***	.0391***	.0610***	-.3030***
Formality of employment						
Informal employment(reference)						
Formal employment	.1500***	.1771***	-.2491***	.1408***	.1608***	-.2490***
Location type						
Urban(reference)						
Rural	-.0753***	-.0958***	.1944***	-0.0866***	-.0954***	.1198***
Constant	3.6119***	3.6668***	1.4230***	3.7550***	3.7798***	1.4592***
Household size		-.0437***			-.0344***	
Mills						
Lambda		-.2373***			-.1590**	

Source: calculations by the authors in Stata with data from the ENOE-INEGI. Probability: * p<.05; ** p<.01; *** p<.001

Those older than the reference interval (16-19 years old) received higher incomes in 2018. Individuals within the 30-39 and 40-49 age intervals earn, on average, 20% and 23% more than those aged 16-19, respectively. It is also found that after the age of 60, a worker continues earning more than a young one, but at the same time their income is marginally decreasing. During the third quarter of 2021, those in the 50-59 group earn 23% more than 16–19-year-olds, slightly higher than the 20% estimated for 2018. It is also observed that in both years, the higher the level of educational attainment, the more income is obtained compared to those who have only studied up to elementary school. In 2021, the income differentials narrow relative to 2018. In 2018, those who had a bachelor's degree in a technical or vocational subject earned 48% more than those who had only primary education; nevertheless, by the third quarter of 2021, the percentage decreased to 44%, indicating a deterioration in the income of those with middle and higher education. When analyzing various variables associated with this segment of the employed population, it is observed that in 2021:Q3, the underemployed population not only grew but exceeded the non-underemployed population. On the contrary, in 2018:T3, the non-underemployed population was larger than the population that was in an underemployed condition. Following the Covid-19 health crisis, the composition changed. In addition, it is found that during 2021:T3, the population working in critical or precarious conditions grew. Both events could have deteriorated the rate of return on schooling for those with technical training, vocational education, or higher education. The decline is also likely to be related to the contraction experienced by the labor market at the time of the crisis. Another feature identified in 2021:T3 is that the number of employed people with a high level of automation, i.e., who are susceptible to being affected by technological change, increased.

For both years, it is estimated that individuals residing in the Northern, Central, Capital, Southern, and Yucatan Peninsula regions receive less income than those working in the states that make up the Northern Border region. The exploratory analysis of the data shows that in both years and quarters, the average income of workers in the Northern Border was higher than the average income of the rest of the regions. In addition, the Border region was dominated by formal employment in both periods, and the figures are higher than those reported by the rest of the regions. Another feature that may help to understand the estimation results is the fact that the Northern Border during 2018:Q3 had, on average, a lower Critical Conditions of Occupation Rate (TCCO; Spanish: Tasa de Condiciones Críticas de Ocupación) than the rest of the regions, except for the Central region. During 2021:Q3 it is also one of the regions with lower TCCO.

It is important to note that the income differential of the Northern, Central, and Capital regions compared to the Northern Border is less than that of the Southern and Yucatan Peninsula regions. The Southern region shows the greatest wage deterioration compared to the Northern Border. In 2018 it received, on average, 38% less, and in 2021, 39%. This figure reveals a deep gap between the Northern Border and the country's Southern region, comprised of Guerrero, Oaxaca, and Chiapas, three states with the greatest social backwardness. The 2018:T3 statistics reveal that this region comprises three states, and the average monthly income is among the lowest compared to the Northern Border, even lower than that recorded in the North, Central, and Yucatan Peninsula regions. In 2021:T3 the same phenomenon is observed, except that the average income differential between the Northern and Southern Border increased

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just after the COVID-19 pandemic. A relevant feature of these two regions is that most employment is formal in the Northern Border. In contrast, in the Southern region, informal employment predominated, increasing more than formal employment during 2021:T1. It is important to note that average earnings in the informal sector are lower than in the formal sector.

In both periods, construction workers receive higher incomes than those working in commerce, services, and agricultural activities. The largest gap is in the agricultural sector and commerce compared to construction. It should be noted that although there is a very prosperous entrepreneurial agricultural sector in the country, the bulk of agriculture in Mexico continues to be for self-consumption and has serious capitalization and productivity problems. Agribusiness, which is high-tech, export-oriented, and extensive, is no stranger to the production of basic grains. Nevertheless, it is strongly oriented toward the production of vegetables and legumes. Some areas with these characteristics are, for example, the Mexicali Valley and the San Quintín Valley in the State of Baja California.

Nevertheless, states such as Sonora, Sinaloa, Jalisco, and Michoacán stand out for their export-oriented agriculture. According to INEGI, Mexico's agri-food zones are divided into five zones: the Northwest, Northeast, Midwest, Center-West, Central, and South-Southeast, in each of which, just as agriculture for self-consumption is typical, there are also very dynamic areas. For example, the Yaqui Valley in Sonora is part of the Northwest region. The Central-West region, which includes Jalisco and Michoacán, is a major producer of avocados, a highly exportable product.

In 2018, the incomes received by workers in commercial and agricultural activities were 38% and 39% lower compared to the construction industry. These percentages for 2021 were 39% and 40%, respectively. In the two years, women, on average, earned 12% and 10% less than men, respectively, and self-employed workers earned 5% and 6% more than subordinate workers. A worker in the formal sector earned 17% and 16% more than an informal worker in the same years, and income conditions in rural areas were more unfavorable for the different groups of workers. Estimates indicate that those with medium and high levels of automation in their occupations during 2018 earned, on average, 25% and 30% less than those with low levels of automation, respectively. It should be considered that workers with a low level of automation are those whose probabilities are less than or equal to 0.3 and are characterized by performing highly specialized tasks.

They are therefore unlikely to be replaced by technology; rather, a process of complementarity would operate. By the third quarter of 2021, the percentages change to 23% and 28%, respectively. The income differential is not only explained by technological change, expressed through the degree of automation of occupations, but also by regional diversity, gender, occupation type, and economic activity sector. It is important to promote local development in those regions with the greatest social backwardness, improving health services, access to decent housing and raising the quality standards of basic education. At the same time, greater infrastructure development should be carried out to promote business development and the generation of formal employment in the country's different regions. The agricultural sector must be strategic and prioritized to improve welfare, especially in the most vulnerable regions. One of the country's most vulnerable regions in terms of poverty and inequality is the southern region, whose development contrasts with other geographic regions, such as the northern border. The South is a region with a strong agricultural sector. It is essential to accelerate agro-industrial activities in tune with local production patterns. Insofar as agriculture and agro-industry consolidate a higher level of development, living conditions will improve, and the levels of social backwardness that prevail in this region will be reduced.

Business development policies should be implemented in accordance with the most pressing needs of the least developed social sectors. Industrial localization programs and projects should be promoted in rural areas and communities with the highest indicators of multidimensional poverty and social backwardness. Rural Mexico must become more prosperous and enjoy greater social justice. Labor policy is an appropriate way to implement programs and actions that favor groups of workers with lower levels of job skills, implementing local and community-based training and education programs that allow them to deploy greater capacities in the work environment. These measures and policies must be long-run and not depend on political cycles. Long-run planning must be conceived as a bastion of social development.

Conclusions

The objective of the research has been to estimate income functions that enable the analysis of inequality among workers with different levels of automation in occupations. Information from the ENOE related to the third quarter of 2018 and 2021 has been used. According to standard theory, the effects of technology on low-skilled workers are not favorable, resulting in wage differentials between skilled and unskilled workers. For this approach, a skilled worker has a completed college degree. In this paper, the educational level has not been considered an indicator of proximity to a technological change variable. Labor occupations and their level of automation have been considered following the methodology of Frey and Osborne (2017). The variable of interest is the monthly earnings of workers, and the key explanatory variable is the probabilities of automation that enable different skill levels to be established. Although technological change is a dynamic process, it is assimilated because it leads to meaningful changes only in the long run.

The results indicate that those who register a medium and high level of automation perform tasks that are more routine or less abstract, requiring a lower level of specialization. These are occupations that are more likely to be replaced by technological processes. The results reveal that in both years, the income differentials operated in favor of specialized work; nevertheless, in 2021:T3, the gap closed slightly, which could be due to the contraction experienced by the labor market at the time of the pandemic. In this context, the essential idea is not to limit the use of new technologies that can trigger more efficient and competitive production processes but rather to think about strengthening the segment of workers with a high level of automation, which in Mexico is around 58%, so that they can acquire new competencies, skills, and abilities. It must be considered that in the Mexican economy, due to its sectoral and business structure, not all work can reach a low level of automation since occupations are highly heterogeneous. In terms of the income gap, it would not be desirable for it to widen, but on the contrary, to gradually narrow it. A considerable increase in the gap would translate into a greater divergence in income levels by the level of automation.

Technological change is unstoppable and continues to advance at an accelerated rate due to innovation and scientific and technological research efforts. It is essential to continue strengthening the labor force's specialization levels to raise schooling and job training levels. In this context, the results indicate that the labor force must continue to strengthen its levels of training; it has been observed that having technical or higher education improves the rate of return on education. Education policy in the different regional areas must be based on wider coverage of the population and higher quality in the teaching processes. In sectoral terms, it is important to start public policy measures that help strengthen the performance of the most depressed sectors, such as agriculture and livestock, where the lowest income differentials are identified compared to construction.

Specific policies should be outlined to revive agricultural production, especially traditional agriculture, and make it more competitive. Support programs for acquiring inputs and technical assistance promoting cropping patterns could be important contributions. At the regional level, the income differences between the Northern and Southern Border regions are considerable and offer a panorama of the asymmetries that exist at the national level. Starting large-scale infrastructure and communication projects can trigger greater investment and social development flows in the three states with the greatest poverty and social backwardness. This does not mean downgrading other regions in terms of financial assistance for development but better focusing on the poorest areas to direct with greater impact the support that will foster the economic and social development of the regions.

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