Technological change and employment following the coronavirus disease (COVID-19) pandemic in Mexico[1]

María Belén Conde, Agustín Filippo,
Carlos Guaipatin and Lucas Navarro

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Abstract

This paper presents an analysis of employment in Mexico from the perspective of exposure to technological change following the recession caused by the coronavirus disease (COVID-19) pandemic. Data from official household surveys from the first quarter of 2019 to the second quarter of 2022 are used, as well as indices measuring the ease of automation of occupations in the country and the possibility of them being performed remotely. Although no effects of technological change are observed at the level of aggregate (formal and informal) employment, in the formal sector, which is more exposed to the adoption of new technologies, employment growth is lower in occupations at high risk of automation and higher in those that can be performed remotely.

Keywords

Employment, labour market, technological change, automation, COVID-19, pandemics, employment creation, employment statistics, Mexico

JEL classification

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Authors

María Belén Conde is a research assistant at the Heldrich Center for Workforce Development at Rutgers University (United States). Email: mb.conde@ejb.rutgers.edu.

Agustín Filippo is Lead Economist at the Inter-American Development Bank. Email: agustinf@iadb.org.

Carlos Guaipatin is Lead Specialist in science, technology and innovation at the Inter-American Development Bank. Email: cguaipatin@iadb.org.

Lucas Navarro is an associate professor in the Department of Economics at the National University of Córdoba in Argentina. Email: lucas.navarro@unc.edu.ar.

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I. Introduction

The economic shock caused by the COVID-19 pandemic had an unprecedented impact on global labour markets (Organisation for Economic Co-operation and Development [OECD], 2021). Like other countries, Mexico experienced the greatest impact during the second quarter of 2020, when lockdown measures were most stringent (Filippo et al., 2021; Hoehn-Velasco et al., 2021). Subsequently, employment recovered, and by the end of 2021, it had exceeded pre-pandemic levels. However, by mid-2022, there were still segments of the working-age population that had been unable to re-enter the labour market.

A comprehensive indicator of labour underutilization that takes this group into account is the employment gap (Kaplan, 2021), defined as the sum of people who are unemployed, underemployed and inactive (not seeking work) but are available to work (the economically inactive population), in relation to the potential economically active population.[2] The employment gap in the second quarter of 2022 stood at 21.7% of the potential economically active population, a substantial recovery compared with 2020 levels, although it was still two percentage points higher than in the fourth quarter of 2019 (see figure 1).

Figure 1
Mexico: employment gap, first quarter of 2019–second quarter of 2022[a]
(Percentages of the potential economically active population)

Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography.
Note: The employment gap is the ratio of the total number of persons who are unemployed, underemployed and inactive (not seeking work) but available to work (economically inactive population) to the potential economically active population.
[a] Data for the second quarter of 2020 are not included.

The data show that the employment gap is significantly higher among women than men, with the most influential factors being underemployment and the available economically inactive population.[3] Although employment in Mexico rose steadily after the pandemic, there was a sharp

[2] The potential economically active population is defined as the sum of economically active people and people who are not economically active but are available to work, which is a measure of "hidden unemployment".

[3] Although these data are available, they are not presented in the current version of this paper. When age groups are considered, the employment gap is found to have a much greater impact on people at the extreme ends of the employment life cycle (ages 15 to 29 and 50 and over).

increase in the number of people who worked less than 35 hours per week but were available to work more (underemployed), and in the number of people who had stopped looking for work but were willing to work (available economically inactive population). Therefore, the fact that the employment gap remains above pre-pandemic levels could reflect weaknesses in employment opportunities for certain population groups.

With regard to the factors that cause structural change in employment, much of the literature produced since Schumpeter (1934) indicates that recessions lead to the acceleration not only of job destruction and business closures, but also of technological change. Therefore, companies take advantage of recessions to adopt new technologies, given the lower labour and opportunity costs during these periods (Kopytov et al., 2018). These technological changes have an impact on the labour market: the data show that, since the 1980s, job losses during recessions in developed countries have occurred primarily in routine occupations that are easy to automate (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). During recovery phases, however, this type of employment remains stagnant, while high- and low-skilled jobs grow, contributing to job polarization (Jaimovich and Siu, 2020).

In the particular case of the COVID-19 pandemic, the need for greater physical distancing in production processes boosted the incentives —typically seen in recessions— to adopt new technologies, affecting the dynamics of job creation and destruction. These new technologies took various forms, such as automation, the digitalization of tasks and the adaptation of processes to facilitate remote work (Apedo-Amah et al., 2020; Brynjolfsson et al., 2020).

The Mexican labour market is an interesting object of study, as some of its characteristics, such as a high level of informality and low labour costs, do not favour the adoption of new technologies (Beylis et al., 2020; Cerezo García et al., 2020). There is also a formal segment, which is driven by competitive sectors integrated into global value chains, and which is more exposed to new technologies (Artuc et al., 2019; Waddle, 2021).

On the basis of data from the National Survey of Occupation and Employment (ENOE) for the period between the first quarter of 2019 and the second quarter of 2022, this analysis explores employment trends across occupations with varying levels of exposure to technological change, at the height of the pandemic-related recession and over the following two years. To that end, variables are used that approximate automation risk, the degree of routinization and the feasibility of remote work for occupations in Mexico.

The results show that, after controlling for observable worker characteristics, there is no evidence, at the level of aggregate (formal and informal) employment, of slower growth in automatable occupations involving many routine tasks, nor of growth in jobs that can be performed remotely. However, when the analysis is limited to the formal sector, which is potentially more exposed to technological change, there is an observable trend towards lower employment growth in occupations with a higher probability of automation and higher employment growth in occupations that allow remote work.

As discussed in the literature review, the relationship between technological change and employment has been extensively studied in developed countries, where automation has had a differential impact on labour demand, increasing the demand for highly skilled jobs and decreasing the demand for more routine and automatable jobs. In Latin America, a series of recent studies have examined how the COVID-19 pandemic may have accelerated these processes in economies with production structures and labour markets that differ from those of advanced countries. Egana-delSol et al. (2022) analysed the case of Chile and determined that, after the health crisis, greater job losses occurred in the occupations with the highest likelihood of automation, although this effect was mitigated in sectors with a high capacity for remote work. Labour costs are higher and

informality levels are lower in Chile than in Mexico, which may have promoted greater automation in Chile in response to the crisis. Similarly, Bonilla-Mejía et al. (2023) show that, in Colombia, the pandemic amplified the reduction in employment in sectors at high risk of automation, particularly in medium-skilled occupations.

This paper complements the existing literature by analysing the case of Mexico, a country with a dual production structure, in which sectors that are highly integrated into global value chains coexist with an economy characterized by high levels of informality and low labour costs. The study is consistent with previous literature in that it provides data showing that the impact of the pandemic on employment differed depending on an occupation's likelihood of automation and its ability to be performed remotely. However, unlike in Chile and Colombia, where a greater number of automatable jobs have been destroyed, in Mexico, informality seems to have slowed this process. This paper is structured as follows: section II, following this introduction, contains a literature review; section III includes a description of the data; section IV outlines the empirical strategy; section V presents the results; and section VI sets out the conclusions.

II. Literature review

According to the International Federation of Robotics, 4,600 industrial robots were installed in Mexico in 2019. Although this is a small number compared with the more than 33,000 in the United States and the more than 140,000 in China, it places Mexico ninth in the world rankings for robot installations that year. On the basis of data from the Federation on the United States, Acemoğlu and Restrepo (2020) determine that each additional industrial robot replaces 3.3 jobs across the economy.[4] Some authors believe, however, that, although the development of robots may be disruptive, its effects on the labour market are not necessarily negative (Leigh and Kraft, 2018). Leigh et al. (2020) also detect gains in manufacturing employment as a result of the inclusion of robots in production in the United States. Dauth et al. (2021) find, on the basis of data from Germany, that although exposure to robots has a displacement effect on manufacturing employment, this effect is completely offset by the reallocation of workers towards the services sector, where employment levels are higher and productivity exceeds that of the jobs destroyed.[5] Corrocher et al. (2023) present data on the geographical and sectoral distribution of automation through robots and artificial intelligence, which is classified as labour-saving, based on a natural language processing methodology applied to the universe of patents in the United States between 1976 and 2021. The authors conclude that robots still account for a minority of automation patents, and are concentrated in a few geographical areas and sectors. In addition, there has been an increase in the number of automation patents aimed at labour savings since 2010.

The labour market has two well-documented features associated with technological change: job polarization and jobless recoveries following recessions.[6] Job polarization refers to the process by which employment increases in high- and low-skilled occupations but decreases in medium-skilled occupations. Jobless recoveries describes periods following recessions during which aggregate output recovers but employment recovers very slowly. Jaimovich and Siu (2020) argue

[4] The authors suggest that, in the next phase of automation, which will be driven by machine learning and artificial intelligence, inequality could be exacerbated unless technological advances are properly harnessed by governments and guided by public policy. Artificial intelligence can lead to job losses if it is not accompanied by technologies that make it easier to learn and use.

[5] Acemoğlu et al. (2014), however, find that industries with more intensive use of information and communications technologies have not performed better in terms of total factor productivity, output or employment. Acemoğlu (2021) argues that one reason is that automation could be excessive, as those who adopt it ignore its effects on job losses.

[6] Data on job polarisation mainly correspond to developed countries, but the phenomenon also occurs in developing countries (World Bank, 2016).

that the two phenomena, jobless recoveries and job polarization, are related.[7] Using data from the United States, the authors show that, since the mid-1980s, when the information and communications technology revolution began, job polarization has increased during recessions. They also find that routine jobs were the most affected during recessions and never recovered. Non-routine jobs (both high- and low-skilled), however, experienced small declines and recovered quickly. Therefore, jobless recoveries are largely due to the disappearance of routine occupations, which represent a significant share of total employment. The authors find similar results when using State-level data from the United States as well as data from a broader sample of countries.[8] The conclusion is that recessions are a catalyst for the adoption of new technologies that affect different types of employment.

On the basis of this background, a growing body of research suggests that the effects of the pandemic may have accelerated previous trends towards automation, the digitalization of activities and remote work, factors that have an impact on employment (Lund et al., 2021). In that regard, according to Weber Handwerker et al. (2020), investment in new technologies has increased owing to the recession caused by the pandemic, because the fixed costs for investment in technology have fallen as economic activity has declined.[9] However, these incentives for adopting new technologies in response to the health crisis differ depending on the infection risk faced by workers in various occupations and sectors, just as the technical possibilities for automation vary between industries, depending on the prevalence of routine jobs.[10]

One unprecedented and noteworthy development is that the distancing measures adopted during the early stages of the pandemic accelerated the adoption of remote working. For safety reasons, many people abruptly switched to remote work, and companies had to adapt and change their processes to facilitate this new way of working (Brynjolfsson et al., 2020). Furthermore, it is believed that the influence of the pandemic as a catalyst for the expansion of remote work will largely persist over time (Barrero, et al., 2021). In that regard, Davis et al. (2021) predicted that, once the pandemic was over, highly skilled workers would spend 30% of their time working remotely, three times more than before the health crisis.[11]

1. Conditions for automation and the impact of the COVID-19 pandemic in Mexico

In the case of Mexico, Cebreros et al. (2020) use the methodology of Frey and Osborne (2017) to measure the number and type of workers employed in occupations at risk of automation. On the basis of data from ENOE, they conclude that 65% of total employment and 57% of formal employment are at high risk of automation in Mexico.[12] The authors acknowledge, however, that these data do not take into account the fact that, when making decisions about automation, companies consider

[7] Similarly, Groshen and Potter (2003) link this slow recovery in employment to structural changes in the labour market resulting, among other factors, from technological change and the reorganization of production.

[8] Blit (2020a) finds similar data for Canada.

[9] Caselli et al. (2020) find that industries in Italy with a higher number of robots per worker recorded fewer infections.

[10] Blit (2020b) believes that the retail, manufacturing, wholesale and transportation sectors may have undergone the most significant transformations. Ding and Saenz-Molina (2020) suggest that automatable jobs in the high-contact service sector may also have been affected.

[11] Using data from March to May 2020 on the share of tasks that can be performed remotely in the United States and the United Kingdom, Adams-Prassl et al. (2022) determine that the tasks that can be performed remotely vary considerably both between and within occupations and industries. During the pandemic, the share of workers who can perform all tasks remotely increases most in occupations in which the pre-existing share was already high. Lastly, within occupations and industries, they find that women and workers on temporary contracts can perform fewer tasks from home.

[12] It should nevertheless be clarified that the Frey and Osborne (2017) index is a maximum estimate of the risk of automation for two main reasons: first, because it considers occupations as a whole and ignores the fact that only certain tasks within those occupations can be automated (Arntz et al., 2016, 2017), and second, because it focuses on the technical feasibility of automation without considering the incentives for automation.

the relevant costs and benefits. It is therefore to be expected that low wages —in relation to the cost of new technologies— as well as low-skilled human capital, high levels of informality and the prevalence of small and medium-sized enterprises in the formal sector will slow down the automation process (Cerezo García et al., 2020).

Filippo et al. (2021) underscore the severity of the impact on women and young people in Mexico, considering the monthly variations in employment that accompanied the economic fluctuations. According to their analysis, widespread lockdowns led to a catastrophic decline in employment regardless of gender, but subsequently, as restrictions were lifted, the phased approach to reopening prioritized more remote activities over those more dependent on physical presence, which are mainly performed by women, thus delaying employment recovery for women. Hoehn-Velasco et al. (2022) find that employment recovery after the pandemic was slower among women than men, and that most employment gains have been in the informal sector, suggesting a possible increase in job insecurity.[13] Juárez and Villaseñor (2024) conclude that women with young children at home experienced additional negative impacts due to the closure of schools and day-care centres, as the increased demand for care at home affected their participation in the labour market.

III. Data

1. Description of the National Survey of Occupation and Employment

The National Survey of Occupation and Employment (ENOE) of the National Institute of Statistics and Geography (INEGI) is used throughout this study. The new version of ENOE, which was established in the third quarter of 2020, contains monthly and quarterly data for the Mexican labour market. This information is obtained by tracking, for five consecutive quarters, a group of people aged 15 and over, who form a rotating panel, one fifth of whose members are replaced by new members each quarter. This survey, conducted in person, provides information about the labour force, employment, informal employment, underemployment, unemployment and other social and demographic characteristics of the members of the households surveyed.

The ENOE survey is available from the first quarter of 2005 to the first quarter of 2020, as INEGI suspended in-person data collection in April 2020 owing to the COVID-19 pandemic. However, in order to obtain information for the second quarter of 2020, the Telephone Survey of Occupation and Employment was conducted during that period only. Subsequently, starting in the third quarter of 2020, the National Survey of Occupation and Employment, New Edition (ENOEN), began to be conducted, using a mixed data collection method (in person and by telephone).

According to INEGI, the information from the Telephone Survey of Occupation and Employment is not comparable with that from ENOE and ENOEN (National Institute of Statistics and Geography [INEGI], 2021).[14] Therefore, this study does not use data from the second quarter of 2020, which is the period during which widespread lockdown measures were imposed in Mexico.[15] The main

[13] Albanesi and Kim (2021) find that women, particularly those who are married with children, were the most affected by the pandemic (Lee et al., 2021). This is because they are overrepresented in the occupations most affected by the pandemic (Alon et al., 2020), namely, those that involve a high level of contact and cannot be performed remotely.

[14] Although the surveys use the same questionnaires, they are based on different operational strategies. ENOE and ENOEN, however, are comparable, according to INEGI.

[15] Lockdown in Mexico officially began on 23 March (Diario Oficial de la Federación, 2020a) and ended on 30 May, when a phase known as the "new normal" began, during which various sectors of the economy were gradually reopened (Diario Oficial de la Federación, 2020b).

differences between the surveys relate to the method of data collection: in the case of ENOE, in person; in the case of the Telephone Survey of Occupation and Employment, by telephone; and in the case of ENOEN, mixed. According to INEGI, ENOE and ENOEN use the same approach to labour market measurement and are comparable. Even so, the change in data-collection methodology could lead to differences in estimates, particularly when comparing the first and third quarters of 2020. As will be specified below, individual control variables (sex, age, education, marital status and presence of children in the household) are used to mitigate these potential problems, helping to correct for possible differences in the composition of the sample. In addition, State-level fixed effects are incorporated to control for structural changes in the distribution of employment at the regional level.

To control for pre-pandemic effects, data from ENOE for the first quarter of 2019 to the first quarter of 2020 are considered, while to examine the medium-term effects of the pandemic, data from ENOEN for the third quarter of 2020 to the second quarter of 2022 are used, thus creating a sample of people aged 18 to 64 who were employed at some point in time.[16]

Table 1 shows the results. The sample is divided between men and women for the quarters included in the analysis.

Table 1
Mexico: National Survey of Occupation and Employment, first quarter of 2019 to second quarter of 2022[a]

Characteristics	Total		Women		Men	
	Proportion	N	Proportion	N	Proportion	N
Age range						
18–30 years	0.32	757 056	0.31	329 485	0.33	427 571
31–45 years	0.36	844 621	0.37	392 228	0.35	452 393
46–64 years	0.32	756 130	0.32	336 252	0.32	419 878
Education						
Not specified	0.00	2 187	0.00	755	0.00	1 432
Primary education	0.20	472 198	0.19	199 308	0.21	272 890
Secondary education	0.34	795 938	0.34	358 734	0.34	437 204
Upper secondary and higher education	0.46	1 087 484	0.47	499 168	0.45	588 316
Marital status						
Not married or living with a partner	0.40	945 957	0.45	479 439	0.36	466 518
Married or living with a partner	0.60	1 411 850	0.55	578 526	0.64	833 324
Children at home[b]						
No children	0.42	991 040	0.40	423 581	0.44	567 459
Children aged 0 to 5	0.24	556 049	0.24	251 327	0.23	304 722
Children aged 6 to 12	0.31	728 230	0.32	339 151	0.30	389 079
Children aged 13 to 17	0.30	697 821	0.31	325 724	0.29	372 097
Location						
Rural	0.34	798 391	0.32	341 760	0.35	456 631
Urban	0.66	1 559 416	0.68	716 205	0.65	843 211
Economically active population						
Employed	0.85	1 995 769	0.78	820 469	0.90	1 175 300
Unemployed	0.02	52 877	0.02	18 452	0.03	34 425
Economically inactive population						
Available to work	0.04	85 436	0.05	49 135	0.03	36 301
Not available to work	0.09	223 725	0.16	169 909	0.04	53 816

[16] The reason for exclusively including people who had been employed at some point is that occupational characteristics can be identified only for employed people. In other words, the sample does not include people who were unemployed or out of the labour force for the entire duration of the periods indicated.

Characteristics	Total		Women		Men	
	Proportion	N	Proportion	N	Proportion	N
Employment status[c]						
Wage earner	0.61	1 446 518	0.56	588 175	0.66	858 343
Employer	0.04	97 558	0.02	22 179	0.06	75 379
Own-account worker	0.16	388 459	0.16	169 288	0.17	219 171
Non-wage earner	0.03	63 234	0.04	40 827	0.02	22 407
Employment classification[c]						
Formal	0.43	1 018 240	0.38	406 074	0.47	612 166
Informal	0.41	977 529	0.39	414 395	0.43	563 134
Economic sector[c]						
Not specified	0.16	374 478	0.23	241 349	0.10	133 129
Agriculture, livestock farming and other related activities	0.06	143 058	0.02	18 805	0.10	124 253
Extractive industries and electricity	0.01	18 566	0.00	3 193	0.01	15 373
Manufacturing	0.15	349 390	0.13	133 296	0.17	216 094
Construction	0.07	162 379	0.01	7 473	0.12	154 906
Commerce	0.16	385 330	0.19	201 185	0.14	184 145
Restaurants and accommodation services	0.07	166 097	0.09	96 781	0.05	69 316
Transportation, communications and postal services	0.04	105 493	0.01	14 427	0.07	91 066
Professional and financial services	0.06	151 742	0.06	60 944	0.07	90 798
Social services	0.08	187 874	0.11	120 339	0.05	67 535
Miscellaneous services	0.09	207 810	0.11	114 083	0.07	93 727
Government and international organizations	0.04	105 590	0.04	46 090	0.05	59 500

Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad*. https://www.inegi.org.mx/programas/enoe/15ymas.

Note: The total sample size is N = 2,357,807.

[a] Data for the second quarter of 2020 are not included.

[b] Variables relating to the presence of children in the household cover children aged 0 to 17 and may add up to more than 1 in total because each variable corresponds to a specific age range, and households may have children of different ages.

[c] The variables treat as "Not applicable" people who are unemployed or not economically active.

With regard to employability characteristics, the sample is composed mainly of employed individuals, and there is a marked difference between men and women in terms of number of hours worked per week. With respect to employment status, the labour market is made up largely of wage earners, who represent 61% of the sample. As for employment classification, there is a similar proportion of formal and informal workers, although women account for a larger share of informal workers.[17] At the sectoral level, commerce and manufacturing account for the greatest share of employment. In addition, differences between sexes are evident in the composition of employment by sector, with a higher proportion of women in commerce and a greater ratio of men in the industrial sector.

2. Indices of exposure to technological change

To estimate the degree to which employment is exposed to technological change in Mexico, four indices were used to measure the characteristics of occupations: one index relating to their probability of automation (Frey and Osborne, 2017), one index relating to the number of routine tasks that they involve (Mihaylov and Tijdens, 2019), and two indices relating to the feasibility of them being performed remotely (Dingel and Neiman, 2020; Leyva and Mora, 2021).

[17] The ENOE definition of informality, which refers to working in the informal sector, being an own-account worker or wage earner in the agricultural sector, being a non-wage earner or being a paid domestic worker without access to health institutions, is used (INEGI, 2014).

The Frey and Osborne index (2017), developed using data from the Occupational Information Network (O*NET), is based on surveys conducted in the United States among a random sample of people employed in each of the categories of the Standard Occupational Classification (SOC) 2010 system. O*NET provides detailed and regularly updated information on the tasks, required skills and scope of work associated with each occupation. The Frey and Osborne index (2017) measures an occupation's probability of automation on a scale from 0 to 1. Values greater than or equal to 0.7 under the Frey and Osborne automation probability index (2017) are considered to indicate a high risk of automation.[18]

The routinization index developed by Mihaylov and Tijdens (2019) is based on the International Standard Classification of Occupations (ISCO-08) and ranges between -1 and 1. A value of -1 represents occupations that involve only non-routine activities, while a value of 1 represents occupations that involve only routine tasks. The intermediate values represent occupations that involve both types of task, routine and non-routine. Using criteria similar to those applied to define occupations at high risk of automation, values in the top 30% of the index, corresponding to a routinization index greater than or equal to 0.4, are considered to indicate occupations with a higher number of routine tasks, which would be very easy to automate over time.

The teleworkable index developed by Dingel and Neiman (2020) also uses O*NET to estimate which occupations can be performed remotely. Under this index, a value of 1 is assigned to occupations that can be performed remotely, while a value of 0 is assigned to those that cannot.

Lastly, the teleworkable index developed by Leyva and Mora (2021) is also considered. Under this index as well, a value of 1 is assigned to occupations that can be performed remotely and a value of 0 is assigned to those that cannot. Unlike the three previous indices, the Leyva and Mora index was created specifically for Mexico, using criteria different from those used by Dingel and Neiman (2020) and taking into account the occupations included in the National Occupational Classification System of INEGI.

As in the case of ENOE, the occupations of employed persons are classified in accordance with the National Occupational Classification System. The equivalence tables prepared by INEGI were used to match the occupations covered by the Standard Occupational Classification (SOC) 2010 system and the International Standard Classification of Occupations (ISCO-08) with the categories included in the National Occupational Classification System in order to calculate, using the structure of occupations in Mexico, the automation probability index, the routinization index and the teleworkable index (Dingel and Neiman). As a result, the values of these three indices were obtained for each of the more than 400 occupations covered by the National Occupational Classification System. In table 2, descriptive statistics are presented for the four indices used in the analysis. Although the average value of the automation probability index (0.66) suggests a high risk of job automation in Mexico, the average value of the routinization index (-0.36) indicates a relatively low level of routine activities. With regard to the teleworkable indices, the average value of the Dingel and Neiman index is double that of the Leyva and Mora index, a fact noted by Leyva and Mora in their paper. The reason for this difference could be related to the characteristics of a labour market such as that of Mexico, where the spread of information and communications technologies in households is slower (Leyva and Mora, 2021).

[18] According to Brynjolfsson et al. (2018), although most industrial occupations involve tasks that can be automated, very few, if any, occupations can be completely automated. In fact, they indicate that process re-engineering and task reorganization, rather than complete automation, could lead to the significant transformation of jobs in the economy.

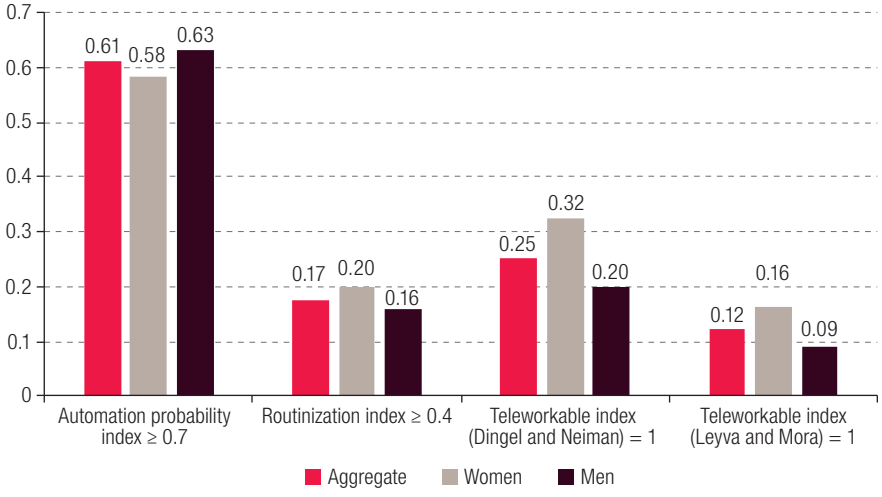
Table 2
Mexico: indices of occupational exposure to technological change, average values from the first quarter of 2019 to the second quarter of 2022[a]

Variable	Mean	Standard deviation	Minimum	Maximum
Automation probability index	0.66	0.31	0.00	0.99
Routinization index	-0.36	0.66	-1.00	1.00
Teleworkable index (Dingel and Neiman)	0.25	0.43	0.00	1.00
Teleworkable index (Leyva and Mora)	0.12	0.32	0.00	1.00

Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad.* https://www.inegi.org.mx/programas/enoe/15ymas.
Note: The total sample size is N = 1,994,955.
[a] Data for the second quarter of 2020 are not included.

Using the indices presented and the criteria mentioned for defining a high risk of automation and a large number of routine tasks for occupations, figure 2 shows the percentage of total jobs in the first quarter of 2020 that have the greatest potential exposure to automation and that can be performed remotely. Occupations at high risk of automation accounted for approximately 60% of pre-pandemic employment, in line with the findings of Cebreros et al. (2020), with the proportion for women being five percentage points lower than for men. Only 17% of the employed population were in occupations involving a large number of routine tasks, with a greater proportion of women than men performing such work. According to a study by the Inter-American Development Bank (Ripani et al., 2020), which used different methodologies, these levels of exposure of Mexican jobs to automation are in the middle range for the region and above those of developed countries. With respect to teleworking, in line with previous estimates for Mexico (Dingel and Neiman, 2020; Alarcón Osuna, 2021; Leyva and Mora, 2021), 25% and 12% of employed persons had jobs that could be performed remotely, in accordance with the teleworkable indices of Dingel and Neiman and Leyva and Mora, respectively,[19] with remote work being more feasible for women than men.

Figure 2
Mexico: employed population exposed to technological change, first quarter of 2020
(Proportion of the total employed population)



Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad.* https://www.inegi.org.mx/programas/enoe/15ymas.
Note: The total sample size is N = 169,256.

[19] As shown by Dingel and Neiman (2020), the percentage of jobs that can be performed remotely is low in Mexico compared with developed countries, and similar to that of other countries in the region.

Table 3 shows that, before the pandemic, more than half of jobs at high risk of automation were held by industrial workers, artisans and assistants, followed by merchants. More than 80% of jobs with a large number of routine tasks were held by two categories of workers: office workers; and industrial workers, artisans and assistants. With regard to remote work, the Dingel and Neiman teleworkable index indicates that more than 70% of jobs that can be performed remotely were held by three categories of workers: (i) professionals, technicians and workers in the arts sector; (ii) merchants; and (iii) office workers. However, under the Leyva and Mora teleworkable index, education workers, civil servants and managers accounted for a greater share of jobs that can be performed from home, with merchants representing a smaller share.

Table 3
Mexico: composition of employment exposed to technological change, by occupation, first quarter of 2020

	Automation probability index ≥ 0.7	Routinization index ≥ 0.4	Teleworkable index (Dingel and Neiman) = 1	Teleworkable index (Leyva and Mora) = 1
Professionals, technicians and workers in the arts sector	0.06	0.06	0.25	0.27
Education workers	0.00	0.00	0.15	0.29
Civil servants and managers	0.01	0.01	0.05	0.11
Office workers	0.13	0.34	0.23	0.23
Industrial workers, artisans and assistants	0.35	0.49	0.04	0.03
Merchants	0.19	0.05	0.24	0.04
Transport operators	0.04	0.01	0.01	0.00
Workers in the personal services sector	0.13	0.03	0.02	0.02
Workers in the security and surveillance sector	0.00	0.00	0.01	0.00
Agricultural workers	0.10	0.01	0.00	0.00

Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad.* https://www.inegi.org.mx/programas/enoe/15ymas.

If the same analysis is performed at the sectoral level, as shown in table 4, results are similar. The manufacturing and commercial sectors account for more than 40% of jobs with a high automation probability index. Furthermore, the manufacturing industry alone accounts for 45% of all jobs involving highly routine tasks. Under the Dingel and Neiman teleworkable index, the commercial and social services sectors account for almost half of all jobs that can be performed remotely. The Leyva and Mora teleworkable index shows a similar result in the social services sector, although the proportion of jobs that can be performed remotely in that sector is much higher.

Table 4
Mexico: composition of employment exposed to technological change, by sector, first quarter of 2020

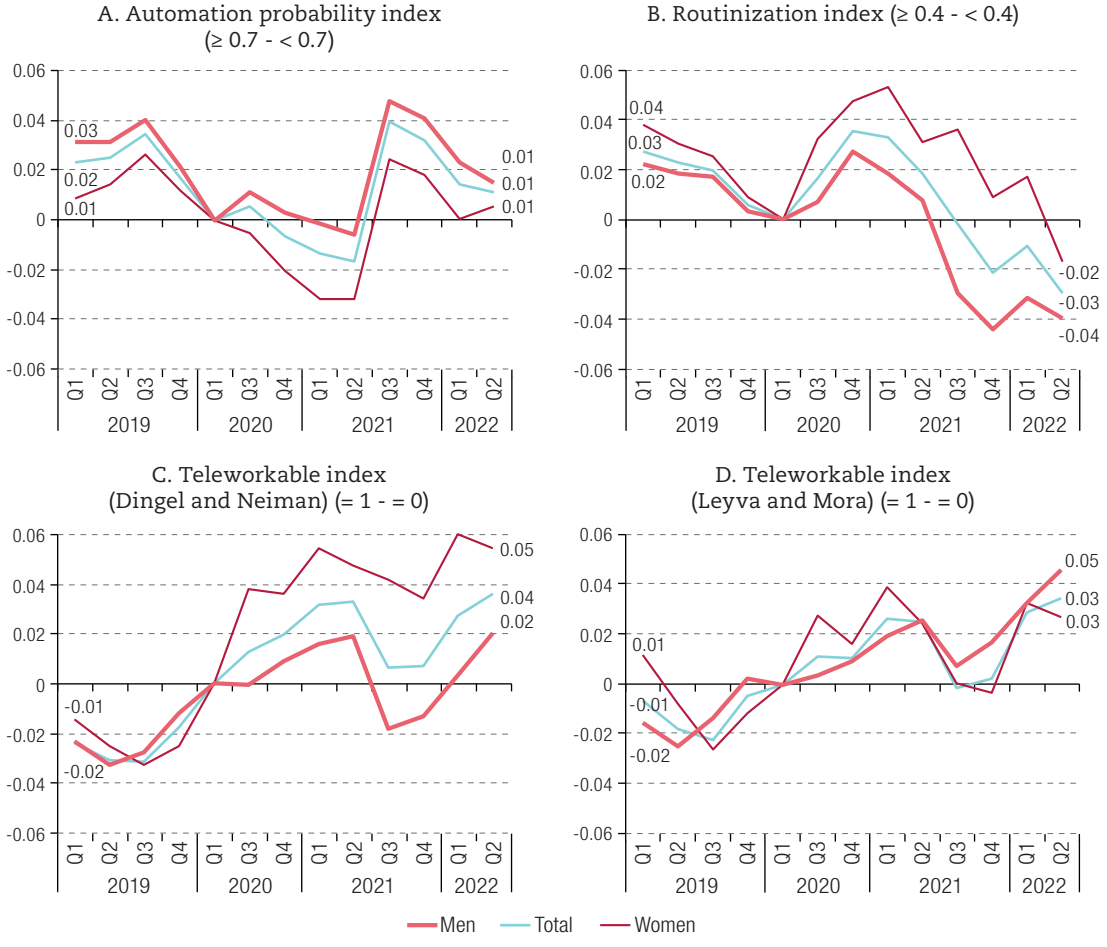
	Automation probability index ≥ 0.7	Routinization index ≥ 0.4	Teleworkable index (Dingel and Neiman) = 1	Teleworkable index (Leyva and Mora) = 1
Not specified	0.01	0.01	0.00	0.00
Agriculture, livestock farming and other related activities	0.10	0.01	0.01	0.01
Extractive industries and electricity	0.01	0.02	0.01	0.01
Manufacturing	0.21	0.45	0.07	0.07
Construction	0.10	0.03	0.03	0.03
Commerce	0.21	0.13	0.25	0.08
Restaurants and accommodation services	0.12	0.04	0.02	0.03
Transportation, communications and postal services	0.04	0.04	0.04	0.04

	Automation probability index ≥ 0.7	Routinization index ≥ 0.4	Teleworkable index (Dingel and Neiman) = 1	Teleworkable index (Leyva and Mora) = 1
Professional and financial services	0.06	0.06	0.16	0.15
Social services	0.04	0.07	0.23	0.40
Miscellaneous services	0.07	0.06	0.04	0.04
Government and international organizations	0.05	0.09	0.14	0.13

Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad*. https://www.inegi.org.mx/programas/enoe/15ymas.

According to the literature, it would be expected that, after the pandemic, employment in occupations that can be performed remotely would have gained momentum. Likewise, any technological change brought about by the pandemic should affect jobs that are at high risk of automation and involve a large number of routine tasks. However, the data for Mexico for the first quarter of 2020 do not reveal a clear difference, at the level of major employment aggregates, between employment growth in the occupations most exposed to technological change and in other occupations. This information is presented in figure 3.

Figure 3
Mexico: comparison of employment growth in the occupations most and least exposed to technological change, in relation to the first quarter of 2020



Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad*. https://www.inegi.org.mx/programas/enoe/15ymas.
Note: The total sample size is N = 1,994,955.

Moreover, although, starting in the first quarter of 2020, employment growth was lower in occupations with a high automation probability index than in other occupations, as expected, this trend reversed starting in the third quarter of 2021. Such differences were small, however, and began to decrease towards the second quarter of 2022. Employment patterns under the routinization index were also erratic, although in the second quarter of 2022, employment growth was lower in occupations involving a large number of routine tasks than in other occupations, with this trend affecting mainly men. Indeed, between the first quarter of 2020 and the second quarter of 2022, men's employment in routine occupations increased by 4 percentage points less than in other occupations.

In addition, there has been stronger employment growth since the first quarter of 2020 in occupations that can be performed remotely, particularly under the Dingel and Neiman teleworkable index, and especially among women: since the first quarter of 2020, women's employment in occupations that can be performed remotely has grown at least five percentage points more than in other occupations. The Leyva and Mora teleworkable index reflects a similar pattern, albeit with stronger growth among men.

In summary, the descriptive evidence suggests that, since the start of the pandemic, the slower growth in employment in occupations at high risk of automation has been temporary. However, employment growth for men in routine occupations has trended down slightly since the second half of 2021, compared with the first quarter of 2020. Lastly, employment in occupations that can be performed remotely grew more than in other occupations. The trends could reflect the effect of other factors not necessarily linked to the exposure of occupations to technological change. This will be considered in the following sections.

IV. Empirical strategy

This section describes the empirical strategy used to analyse employment in occupations with high exposure to technological change, in accordance with the four indices considered, and controlling for characteristics of the individuals in the sample that could affect the trends in the aggregate statistics presented in figure 3.

Microdata from ENOE from the first quarter of 2019 to the first quarter of 2020, and from ENOEN from the third quarter of 2020 to the second quarter of 2022, are used to analyse employment trends in accordance with the various indicators of exposure to technological change presented above, applying the following formula:

$$Y_{i,t} = \alpha + \sum_{\tau=-4}^{8} I(\tau)\{\gamma_\tau + \beta_\tau I_i(E_0)\} + \eta I_i(E_0) + \nu X_{i,t} + \epsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ represents the relevant labour market outcome for individual i in quarter t. The outcome variables considered are employment and formal employment (as dichotomous variables). The variable τ denotes the reference quarter in relation to the pandemic, covering four quarters before the pandemic (from the first to the fourth quarter of 2019) and eight quarters after the pandemic (from the third quarter of 2020 to the second quarter of 2022). The period $\tau=0$ corresponds to the first quarter of 2020, which is the reference quarter. The variable $I_i(E_0)$ is a dichotomous variable indicating a person's level of exposure to technological change at the moment that he or she first appears as employed in the sample; the value of E_0 changes depending on which of the four indices is being used.[20]

[20] Unlike surveys in other countries (such as the Current Population Survey in the United States), which identify the occupations of persons who are employed, unemployed and outside the workforce (Albanesi and Kim, 2021), ENOE only reveals the occupations of employed persons. Therefore, ENOE defines each person's occupation as that held by him or her at the time that he or she first appeared as employed in the sample, retaining that information for quarters in which the person might no longer be employed. As a robustness test, the same analysis was performed using the value of technological exposure variables from the previous quarter. The results were very similar to those obtained from the baseline specification.

The variable $X_{i,t}$ includes a series of controls for social and demographic characteristics such as sex, age, years of education, marital status, presence in the household of children aged 0 to 17 and geographical area. In addition, all regressions include State-level fixed effects.[21] Lastly, $\epsilon_{i,t}$ is an error term. State-level fixed effects control for structural differences and regional dynamics in the Mexican labour market. Given that exposure to technological change can vary significantly between States owing to factors such as sectoral composition, technological infrastructure and degree of urbanization, the inclusion of these fixed effects makes it possible to separate the impact of technological change on employment from other regional determinants. Furthermore, by using data from multiple quarters, State-level fixed effects help to capture unobserved heterogeneity.

The relevant interaction coefficients β_τ measure the difference between people exposed and not exposed to technological change on the basis of the variation in Y between τ and the reference period $(\tau=0)$. For example, in the case of the outcome variable of employment and the automation probability index, if $\beta_\tau>0$, employment growth between the first quarter of 2020 and τ is higher for people in occupations with a high automation probability index than for the rest of the sample.

Lastly, the sample includes only people aged 18 to 64 with any occupational status (employed, unemployed, available to work or unavailable to work), provided that they were employed at some point during the period under review.

V. Results

The results of the estimates are presented in this section. The figures only show the coefficients associated with the interaction term between each quarter and the indices of exposure to technological change from the equation presented in the previous section.

In figure 4, the results are shown using employment status (either formal or informal) as the dependent variable. Starting in the third quarter of 2021, slightly higher employment growth is estimated in occupations with a high theoretical probability of automation but limited actual exposure to automation owing to informality.[22] This apparent paradoxical result may reflect a composition effect, as will be seen later.

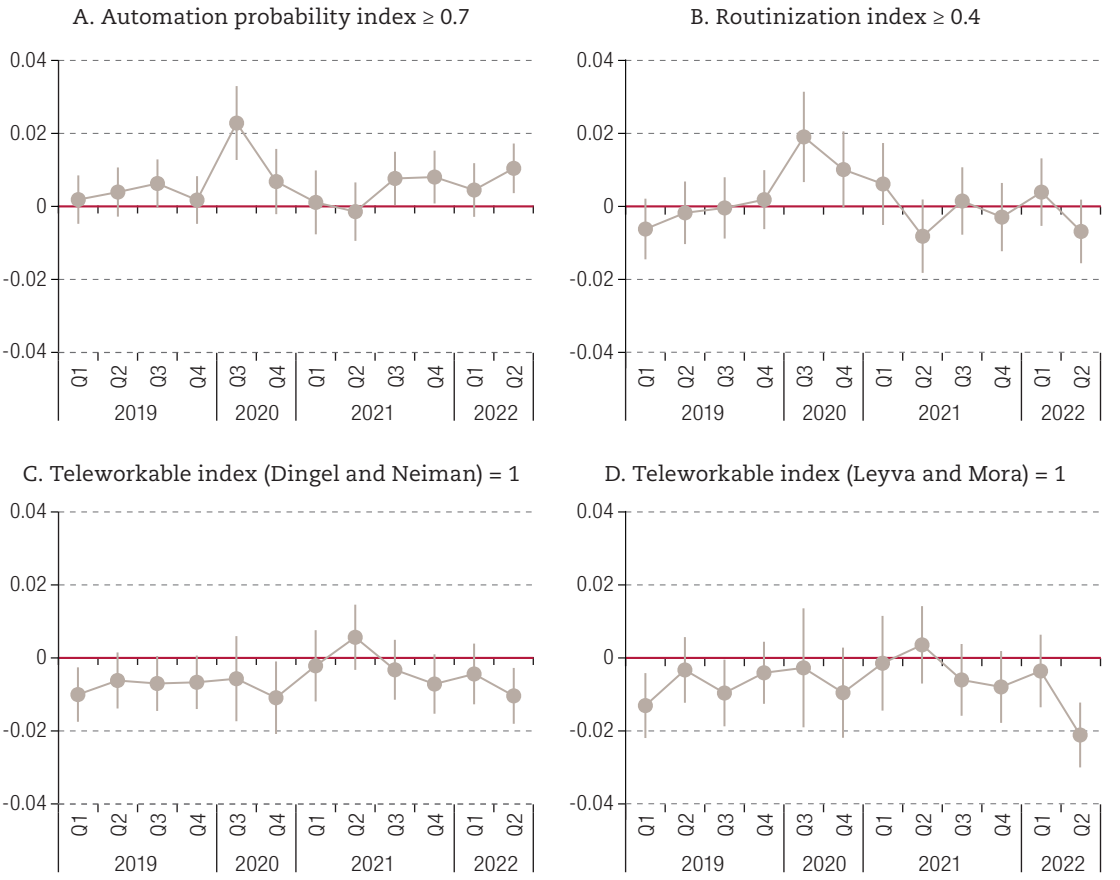
The trend of employment in occupations involving a large number of routine activities does not differ from that of employment in other occupations.[23] There is also no clear increase in remote work at the level of aggregate employment. The results disaggregated by sex, presented in figure 5, are similar.

[21] As mentioned above, ENOE is conducted using a rotating panel, one fifth of whose members are replaced by new members each quarter. This means that not all individuals are present during all periods, making it difficult to identify reliable individual fixed effects. The study focuses, however, on the effect of technological change on occupations rather than on individual changes in the same worker over time.

[22] Almost two thirds of employment at high risk of automation (see table 3) is concentrated in occupations with levels of informality above the average (49% in the first quarter of 2020), such as those performed by industrial workers, artisans and assistants (53%), merchants (62%) and agricultural workers (85%). These occupations recovered more quickly than others after the health crisis (Hoehn-Velasco et al., 2021).

[23] Although the results for the automation probability index and the routinization index appear to be mutually inconsistent, these indices are, by definition, not comparable. The automation probability index classifies entire occupations as automatable, while the routinization index identifies specific tasks that are considered routine and are therefore more likely to be automated (Arntz et al., 2016, 2017). In particular, 73.6% of the observations in the sample with an automation probability index ≥ 0.7 correspond to occupations with routinization index values < 0.4.

Figure 4
Mexico: change in the probability of being employed[a]

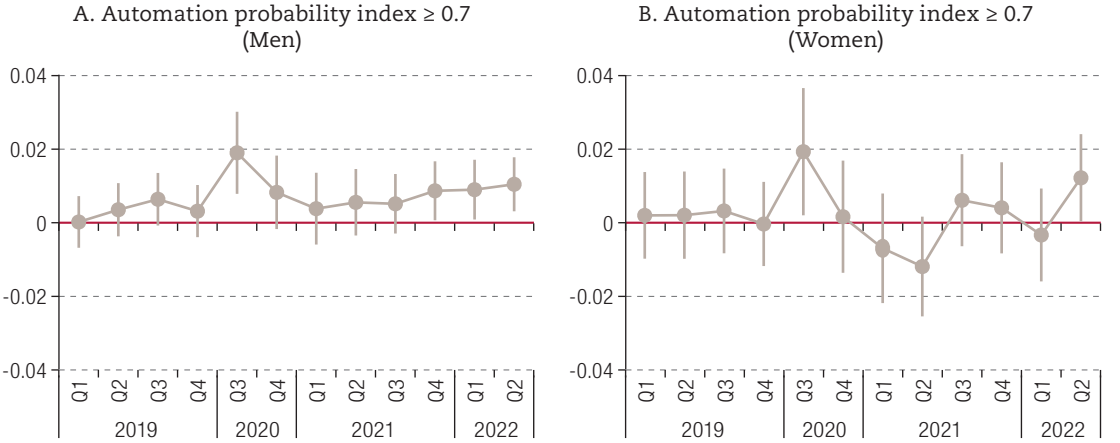


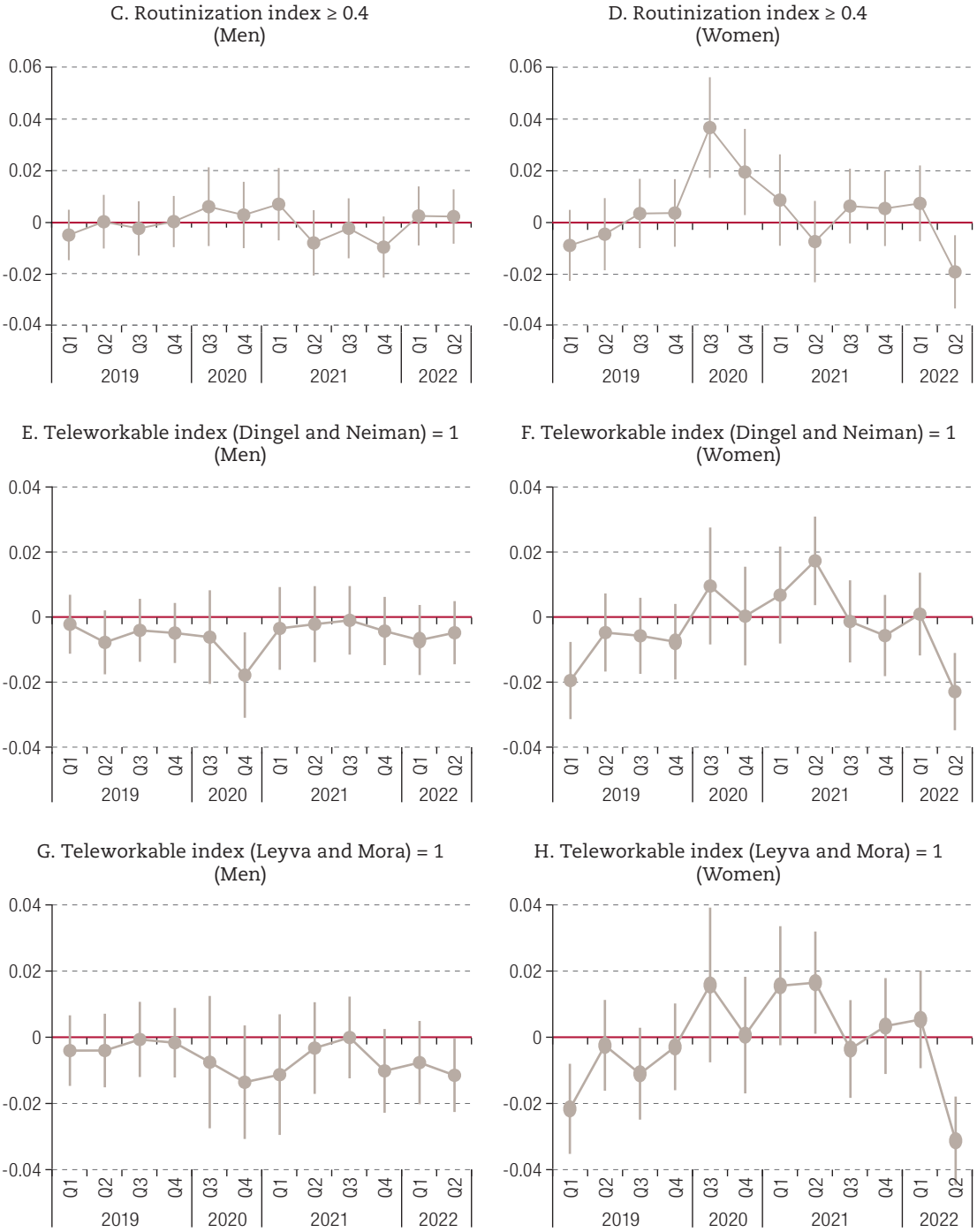
Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad*. https://www.inegi.org.mx/programas/enoe/15ymas.

Note: Estimates obtained using the ordinary least squares method. Standard errors are grouped at the individual level, and vertical lines represent 95% confidence intervals.

[a] Data for the first and second quarters of 2020 are not included.

Figure 5
Mexico: change in the probability of being employed, by sex[a]





Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad.* https://www.inegi.org.mx/programas/enoe/15ymas.

Note: Estimates obtained using the ordinary least squares method. Standard errors are grouped at the individual level, and vertical lines represent 95% confidence intervals. The graphs on the left show the results for men, and the graphs on the right for women.

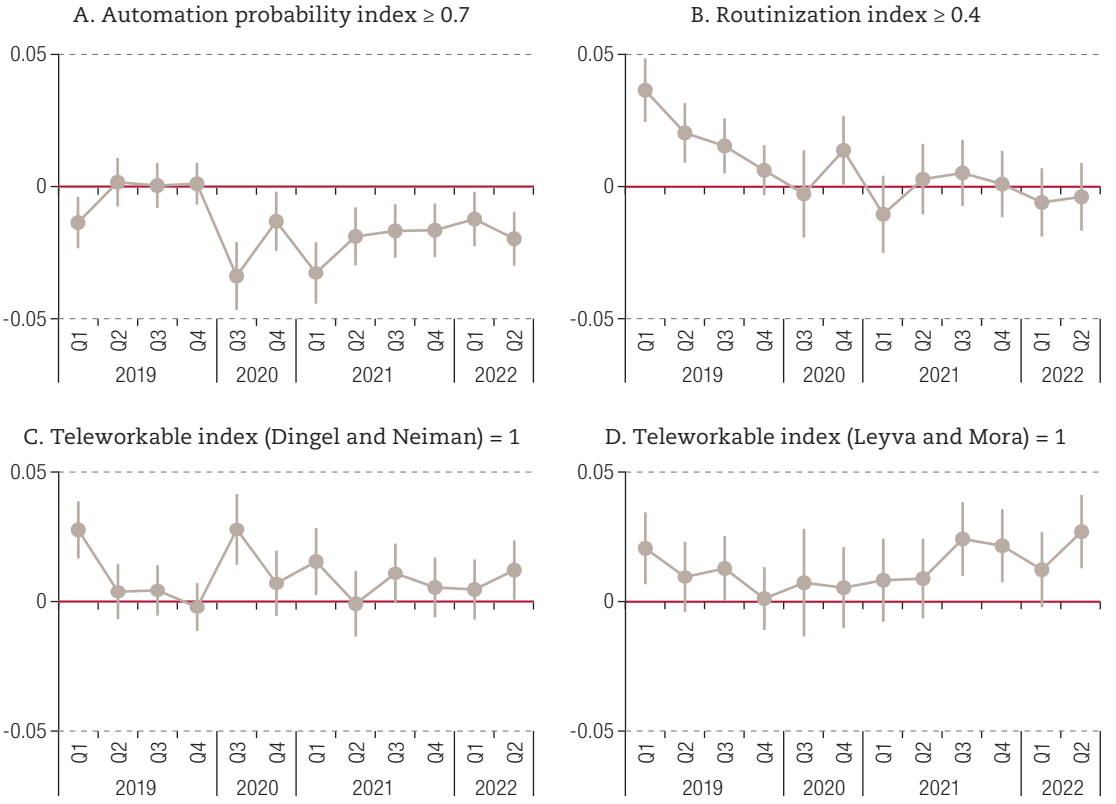
[a] Data for the first and second quarters of 2020 are not included.

As mentioned above, the results presented may reflect an employment composition effect. In the reference quarter (first quarter of 2020), approximately 51% of the people included in the sample (population aged 18 to 64) were employed in the formal sector, compared with 49% in the

informal sector. Given that the adoption of new technologies is more likely to occur in the formal sector of the economy (Cerezo García et al., 2020), the increase in employment in occupations at high risk of automation, reflected in figures 4 and 5, could be occurring in the informal sector.

Figure 6 shows the effect of exposure to technological change on the probability of employment in the formal sector among people who are employed. Since the third quarter of 2020, there has been a statistically significant trend towards lower employment growth (by 2 percentage points in the second quarter of 2022) in occupations with high automation probability indices compared with other occupations. There is no statistically significant difference in employment growth between occupations with a high and low routinization index. Another interesting finding is that the probability of being employed in the formal sector increased more in occupations that can be performed remotely than in other occupations (by between 1.2 and 2.7 percentage points in the second quarter of 2022), especially under the index developed by Leyva and Mora (2021), who analysed the feasibility of remote work for occupations in Mexico.

Figure 6
Mexico: change in the probability of being employed in the formal sector[a]



Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad.* https://www.inegi.org.mx/programas/enoe/15ymas.

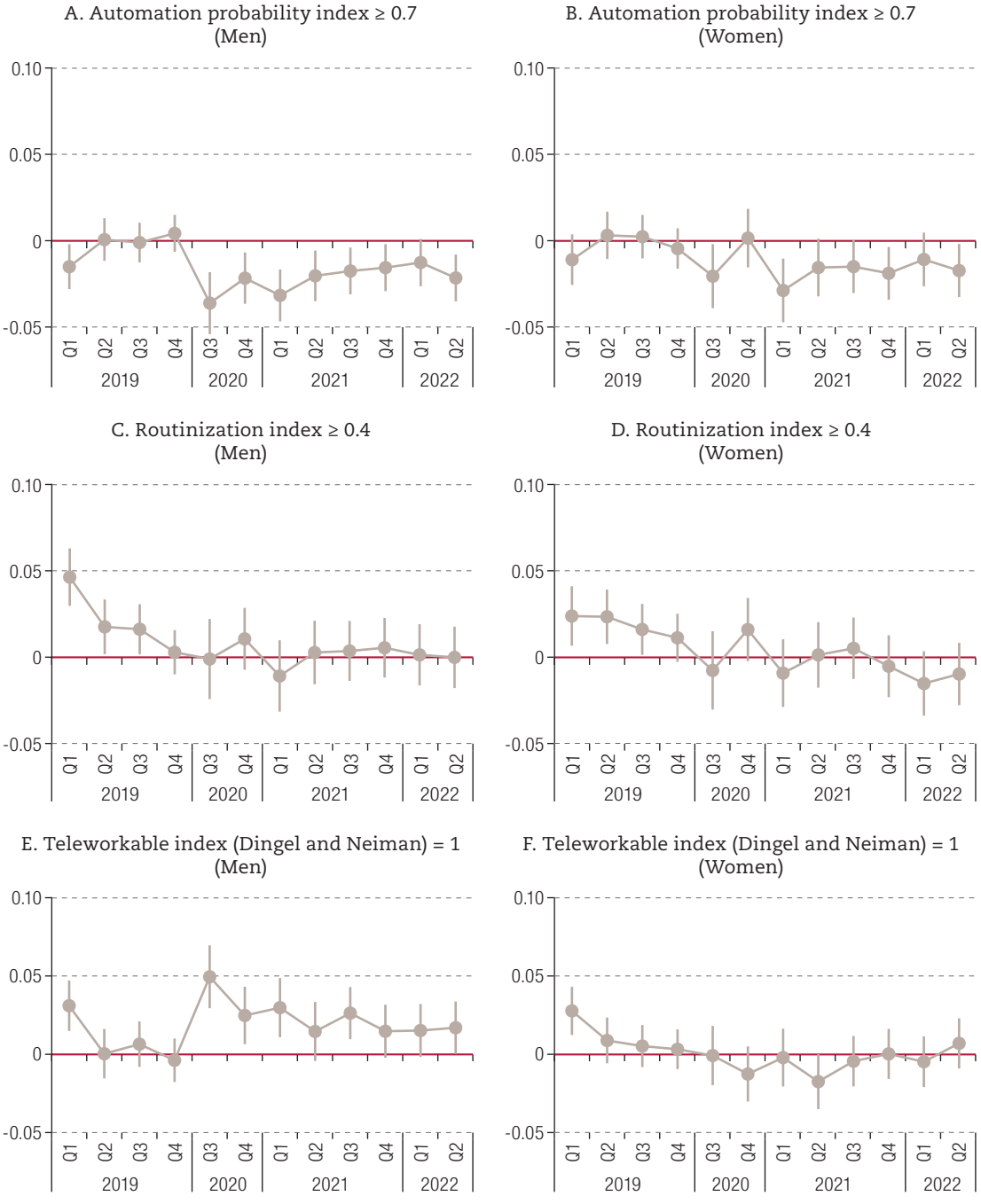
Note: Estimates obtained using the ordinary least squares method. Standard errors are grouped at the individual level, and vertical lines represent 95% confidence intervals.

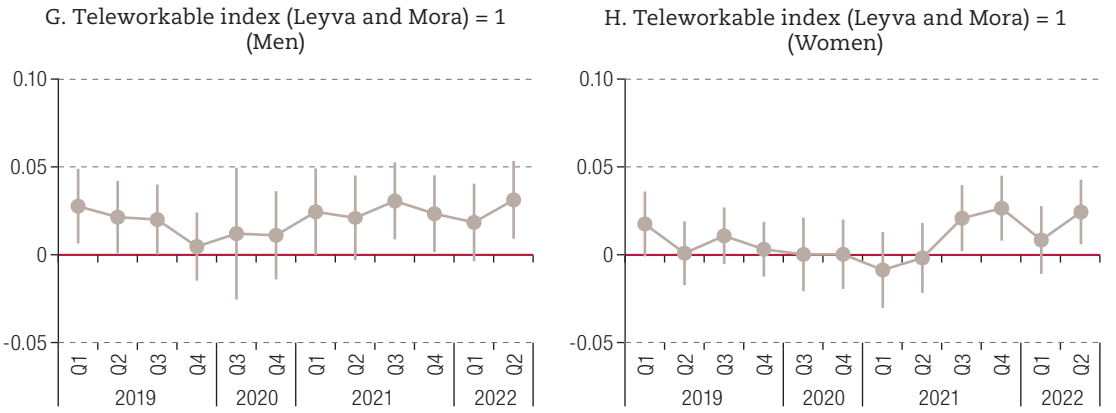
[a] Data for the first and second quarters of 2020 are not included.

Figure 7 presents the same results, disaggregated by sex. The estimates indicate that the growth differential in employment in occupations with high automation probability becomes negative and statistically significant starting in the third quarter of 2020. This pattern is more pronounced among men, although it is also observed among women. The trend towards higher employment

growth in jobs that can be performed remotely is also confirmed. Indeed, the growth differential in employment in occupations with a value of 1 under Dingel and Neiman's teleworkable index in relation to other employment tends to become positive for men starting in the third quarter of 2020, while the effects on women are, on average, indistinguishable from zero. Lastly, the interaction coefficients under the Leyva and Mora teleworkable index are positive and statistically significant with a 95% confidence interval for both men and women, particularly starting in the third quarter of 2021.

Figure 7
Mexico: change in the probability of being employed in the formal sector, by sex[a]





Source: Prepared by the authors, on the basis of National Institute of Statistics and Geography. (2025). *Encuesta Nacional de Ocupación y Empleo (ENOE), población de 15 años y más de edad*. https://www.inegi.org.mx/programas/enoe/15ymas.

Note: Estimates obtained using the ordinary least squares method. Standard errors are grouped at the individual level, and vertical lines represent 95% confidence intervals. The graphs on the left show the results for men, and the graphs on the right for women.

[a] Data for the first and second quarters of 2020 are not included.

In summary, the results of the estimates suggest: (i) lower growth in formal employment in occupations with a high automation probability index, with a slightly greater impact on men than on women; and (ii) higher growth in formal employment in occupations that can be performed remotely, a pattern that is more pronounced among men but also observable among women.

The relationship between technological change and employment means that, in order for effects to be observed on the labour market, companies must be adopting new technologies. Unfortunately, no relevant information is available for the period under review. Sources such as the INEGI National Survey on Productivity and Competitiveness of Micro, Small and Medium Enterprises, which provides data on digitalization and technology use in the business sector, are only available for 2015 and 2018.

Beyond this limitation, the results are consistent with the existing literature in two ways: first, as mentioned above, several studies have shown that economic crises accelerate the introduction of new technologies owing to the need for efficiency and cost reduction (Kopytov et al., 2018; Brynjolfsson et al., 2020); second, the differential impact on formal and informal employment is consistent with what would be expected if new technologies were adopted. Specifically, there is less growth in formal employment in occupations with high exposure to automation and greater growth in employment in occupations that can be performed remotely. These results suggest that, at least in the formal sector, the dynamics are consistent with technological change.

In summary, although it would be valuable to supplement the study with direct information on the adoption of technology in Mexican companies, such information is not available. Current findings suggest, however, that there is a differential impact on formal employment, which is consistent with technological change. Future research could explore this relationship in greater depth by combining labour market data with indicators of investment in automation and digitalization in Mexico.

VI. Conclusions

Considering exposure to technological change, this paper presents an analysis of employment in Mexico following the COVID-19 pandemic using ENOE data from the first quarter of 2019 to the second quarter of 2022, together with indices of exposure to technological change for occupations in the country.

In relation to the first quarter of 2020, there is no conclusive evidence showing a decline in aggregate employment in occupations that have a high probability of automation and involve a large number of routine tasks, nor is there any evidence of growth in aggregate employment in occupations that can be performed remotely.

The results are different, however, when the analysis is limited to the formal sector, where the adoption of new technologies seems more likely. In particular, since the third quarter of 2020, there has been a relative reduction in the creation of formal employment in occupations with a high probability of automation, compared with other occupations. This effect is more pronounced among men, suggesting that automation may have had a greater impact on male-dominated sectors within formal employment. Moreover, growth in formal employment has been higher in occupations that can be performed remotely than in other occupations, especially since the second half of 2021. This effect is most evident when considering a teleworkable index developed specifically for Mexico, suggesting that the pandemic may have accelerated structural changes in the organization of work in certain sectors.

Although effective exposure to technological change still appears to be low, following the pandemic, as expected (Beylis et al., 2020), a series of accelerated changes occurred in the formal labour market that were compatible with the adoption of new technologies. The lack of a broad decline in employment in automatable occupations suggests that the high level of informality in the Mexican labour market may be acting as a buffer against the aggregate effects of automation on employment. Unlike countries with more formal labour markets, where technological progress can quickly translate into job displacement, in Mexico, the presence of sectors with low labour costs and limited access to technology may be slowing this process. However, the effects identified relate to the short and medium term. Over a longer time horizon, at least two additional effects —beyond the scope of this study— may arise. First, the expansion of firms that adopt new technologies may increase labour demand through a scale effect. Second, workers displaced by new technologies should be gradually reallocated to other occupations within the labour market.

Public policy can facilitate these transformations in various ways. In particular, there should be a policy strategy that is focused on productive development and provides incentives for companies to innovate, thereby promoting growth and job creation. In addition, the reallocation of workers towards more productive activities should be facilitated, demonstrating the central importance of policies that promote the training and development of human capital.

In summary, although the pandemic did not cause an abrupt change in the structure of employment in Mexico, the trends indicate that the formal labour market is being slowly but progressively transformed in response to technological change.

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