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Abstract: Based on the methodology proposed by Frey and Osborne (2017), we use their estimates for the probability of automation of occupations together with household survey data on the occupational distribution of employment to provide a risk assessment for the threat that automation may pose to the Mexican labor market. We find that almost two thirds of total employment is at high risk of automation; slightly more than half if we only consider employment in the formal sector. We argue that, while these estimates provide a useful benchmark to start thinking about the impact that automation may have on the labor market, they should be interpreted with care as they are solely based on the technical feasibility to automate and do not reflect the economic incentives, or other factors such as the accumulation of human capital through education, to adopt automation technologies.
Keywords: Automation; Human capital and occupational choice; Labor demand; Organization of production; Robots; Technological change.
JEL Classification: E24, E26, F16, J21, J23, J24, J62, L23, L86, O33, O38, N16.

Resumen: Con base en la metodología propuesta por Frey y Osborne (2017), utilizamos sus estimaciones de la probabilidad de automatización de ocupaciones junto con datos de encuestas de hogares sobre la distribución ocupacional del empleo para proporcionar una evaluación del riesgo que la automatización puede representar para el mercado laboral mexicano. Encontramos que casi dos tercios del empleo total está en alto riesgo de ser automatizado; un poco más de la mitad si nos enfocamos en el empleo formal. Sostenemos que, si bien estas estimaciones proporcionan un punto de referencia útil para comenzar a pensar en el posible impacto que la automatización puede tener en el mercado laboral, estas deben interpretarse con cuidado, ya que se basan únicamente en la viabilidad técnica para automatizar el empleo y no reflejan los incentivos económicos, u otros factores como la acumulación de capital humano a través de la educación, para adoptar tecnologías de automatización.
Palabras Clave: Automatización; Capital humano y elección ocupacional; Demanda de trabajo; Organización de la producción; Robots; Cambio tecnológico.

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1 Introduction

In this paper we use the distribution of employment across occupations, obtained from household surveys, together with estimates for the 'automatability'[1] of occupations to provide a risk assessment for the Mexican economy regarding the potential disruption that automation technologies may have on the labor market. We estimate that 65 percent of the total employment, and 57 percent of the formal sector employment, is at high risk of being automated. We document considerable heterogeneity across demographic groups regarding the share of employment that is at high risk of being displaced by automation technologies. In particular, we find that younger and less educated workers are the most exposed to this threat. We contend that risk assessments solely based on the technological feasibility of automation are useful as a starting point but may overestimate the extent to which labor will be displaced by automation by not considering the economic incentives to automate. That is, given that automating tasks/occupations is not costless, firms may decide that it is not profitable to do so even if it is technologically possible. For the case of emerging markets with a high degree of trade openness, such as Mexico, we argue that key factors shaping the pace at which automation technologies penetrate the economy, at least in the short run, are: the size of the informal labor market; the economy's wage structure across occupations; and the interaction between technology adoption and parallel processes that affect the re-organization of economic activity, such as offshoring. Given the lack of detailed information on the penetration of these technologies in Mexico and a precise quantification of the tradeoffs between benefits and costs of adoption, the scope of this paper is necessarily confined to exploring the potential channels through which automation might reshape the structure of production and impact labor markets and shedding light on which categories of workers might be exposed to the most severe threat. While we believe that our analysis is interesting and a fundamental first step for understanding the potential socio-economic consequences of transitioning to new technologies, we acknowledge that the data limitations we face at the moment do not permit a more sophisticated identification of the causal/structural/general equilibrium implications of adopting automation technologies.

Substantial advances in the fields of robotics and artificial intelligence (AI) have been a salient phenomenon redefining technological frontiers in recent years.[2] Rapid progress of AI in performing tasks at human-like levels of capability in voice recognition, translation, and

[1] In the recent literature on automation the word automatability has emerged to characterize the technological ability of a task/job/occupation to be automated.

[2] Agrawal, Gans, and Goldfarb (2019) date AI's commercial birth to 2012.

visual image recognition are just a few examples, among a large number of advances, that stand to reshape skill demands, career opportunities, and the distribution of workers among industries and occupations. As such, the impending integration of automation technologies into our daily economic and social activities forces us to evaluate the implications that the adoption of these technologies may have for labor markets and the organization of economic activity. As these technologies progress, more researchers are investigating the question of what labor markets will look like in a world filled with computers and industrial robots that can replicate, or even surpass, many human abilities. In this context, a key concern, particularly for policy makers, is the extent to which automation technologies will replace humans in the economy's productive structure (i.e. 'technological unemployment'). That is, whether AI will completely automate occupations or just automate some, but not all, of the tasks performed within an occupation and to which degree.[3]

The discussion regarding the social costs and benefits of automation can be roughly divided into two key issues: its effect on aggregate welfare and its distributional implications. While in the long run automation technologies, like previous forms of technological change, will likely lead to substantial economic growth and aggregate welfare gains, the adoption of these technologies will probably result in a differential impact across different types of workers in the short run. Workers whose skills/tasks/jobs are complementary to these technologies will benefit, while workers who are substitutable with these technologies will lose out.[4] Nonetheless, it should be noted that the adoption of automation technologies induces several changes at once that result in competing dynamics, some of which lead to job creation and some that result in job destruction. That is, even if automation technologies depress employment for some types of labor, they can also create new opportunities through 'creative destruction'.[5]

The concerns regarding technologically induced labor displacement are not new (see Berg,

[3]See Autor (2015) for an introductory discussion of these and other issues related to the impact of technological progress on labor markets and employment.

[4]Workers who lose from technological progress, in the short run, tend to have lower than average educational levels and reside in areas without diversified sources of employment. See, for example, Smith (2018) for further discussion.

[5]Leading examples of this phenomenon are the introduction of ATMs into banking and the replacement of equestrian travel with automobiles. In the first case, while ATMs automated much of the teller's work resulting in a contraction of employment through the intensive margin (i.e. less tellers at each branch), total bank employment grew due to expansions along the extensive margin. That is, the productivity gains achieved through the introduction of ATMs increased bank profitability and led to the opening of more bank branches that more than compensated for the employment lost at pre-existing branches. In the second case, the introduction of automobiles led to job creation through its effect on the demand for roadside amenities, such as motels, gas stations, and fast food. See Frank et al. (2019) for details and additional discussion. Also see Madrigal (2018) for a discussion on the case of self-driving trucks.

Buffie, & Zanna, 2018; Mokyr, Vickers, & Ziebarth, 2015). However, policy makers still lack effective mechanisms to prevent or reduce the costs of major labor market displacements. Given that automation technologies stand to redefine the relationship between human labor and technology in more drastic ways than what has been previously observed, it is not surprising that there has been a proliferation of research aimed at understanding the various facets of this problem. A particular emphasis has been placed on understanding how and when these technologies will contribute to increasing firm-level and aggregate productivity (see, for example, Acemoglu & Restrepo, 2018a, 2018b; Aghion, Jones, & Jones, 2017; Aum, Lee, & Shin, 2018); the conditions under which automation complements or substitutes labor (see Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2018b; Autor & Salomons, 2018; Lordan & Neumark, 2018, among others); and the kind of policies that can help to mitigate the disruption that the adoption of these technologies may have on labor markets (see Agrawal et al., 2019).[6]

Although no definitive consensus has been reached regarding how automation should be conceptualized and modeled, so far the task-based approach to automation has been the leading framework for thinking about the role of automation in the economy (see Acemoglu & Autor, 2011). From this perspective, the distinctive feature of automation is the use of machines/technology to substitute for human labor in a widening range of tasks. Thus, from this vantage point, automation can be characterized as the expansion of the set of tasks that can be produced by machines (see Acemoglu & Restrepo, 2018b).[7] An important feature of the task-based approach is that it makes a distinction between the intensive and extensive margin of automation. The intensive margin refers to improvements in the productivity of tasks that have already been automated, while the extensive margin refers to the automation of new tasks previously done by humans. At the core of this modeling approach are two separate channels through which automation can affect aggregate employment. On the one hand, the *displacement effect* refers to the direct effect of no longer needing/wanting certain workers. On the other hand, the *productivity effect* is an indirect effect that results from an increase of the scale of operation due to higher productivity and leads to an increased demand for labor. That is, although automation substitutes for labor, it can also raise output

[6]Some of the policy options that have been discussed in this context are: universal basic income; better unemployment benefits; and a social wealth fund, where the government uses taxes to invest in companies that own or benefit from the output of robots/AI, such that each person participates in the ownership of the output generated by automation technologies.

[7]Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2018) analyze the adoption of new technologies during the period 1960-2000, in particular the adoption of ITC technologies, and their impact on labor markets through the effect that these technologies had on non-routine analytic, non-routine interactive, routine cognitive, and routine manual tasks.

in ways that lead to higher demand for labor. Additionally, in a multi-sector model of the economy, regardless of the effect that automation may have on the employment of a directly impacted industry, technology adoption may have spillover effects on labor on upstream and downstream industries. For example, Autor and Salomons (2018) find that, while employment seems to fall within an industry as industry-specific productivity increases, positive spillovers to other sectors more than offset the negative own-industry employment effects.

So far, the seminal paper by Acemoglu and Restrepo (2017) has been the main reference for the empirics of technologically induced labor displacement. Using data from the International Federation of Robotics (IFR), these authors study the impact of the introduction of automation technologies (in the form of industrial robots) on local labor markets. They find that the adoption of industrial robots in the United States was negatively correlated with employment and wages. In particular, for each additional robot, employment decreased by six workers, and an additional robot per thousand workers reduced wages by 0.5 percent. Furthermore, they find that the adoption of robotics did not have a positive effect on any industry and that the negative impacts on employment were most pronounced in manufacturing, among workers without a college degree, and for routine or blue collar occupations. These findings would suggest that the displacement effect induced by automation has been stronger than the productivity effect thus far, leading to a net loss of jobs. However, researchers disagree on whether automation is creating or destroying jobs. Mann and Püttmann (2018) propose an indicator of automation that is constructed by applying a machine learning algorithm to classify patents, and use it to investigate which US regions and industries are most exposed to automation. Based on this approach, these authors find that automation has created more jobs in the United States than it has destroyed.[8]

As previously mentioned, a key concern for policy makers is understanding the kind of policies that can help mitigate the disruption that the adoption of automation technologies may have on labor markets. However, making a diagnostic of the problem is necessary prior to formulating any policy recommendation. This paper aims at complementing the part of the literature that analyze the vulnerability of the economy to 'technological unemployment' by estimating the share of workers whose employment may be at high risk of being automated, and by dissecting the exposure to this threat across industries and demographic groups (see Frey & Osborne, 2017; Nedelkoska & Quintini, 2018). We also contribute to this literature by

[8]Bughin (2018) reports that in a survey of 3000 CEOs —covering 14 industries, 10 countries and inquiring about employment expectations as a result of AI adoption— 10 percent of firms expected an increase in employment; 19 percent of firms expected a reduction of labor with an overall reduction in total employment; 27 percent of firms expected a reduction in employment due to AI that was compensated by new jobs; and 44 percent of firms expected no material change in employment.

considering incentives for the adoption of automation technologies that go beyond technical feasibility but may be particularly relevant for emerging economies such as Mexico.

The rest of the paper is organized as follows. Section 2 briefly describes the data sources. Section 3 presents estimates for the share of employment at high risk of being automated, for the economy as a whole and across different demographic groups, based on the calculations of Frey and Osborne (2017). Section 4 discusses some reasons why estimates in the literature similar to those presented in section 3 may overestimate the extent to which automation will displace workers. Section 5 offers some concluding remarks.

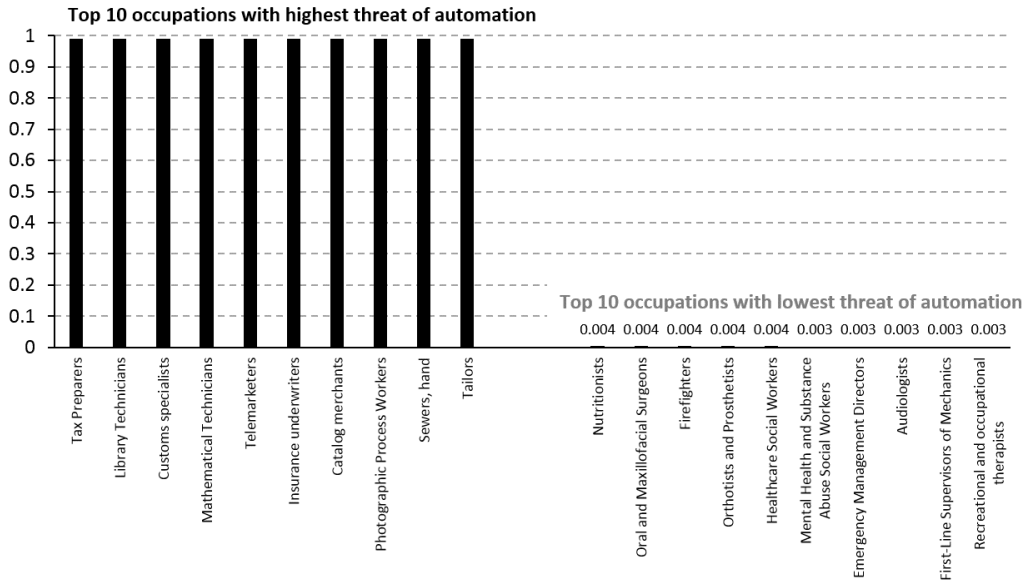
2 Data

In this section we describe the primary data used to produce the results of the empirical exercises presented in section 3. Our results are derived from combining two data sources that allow us to classify workers in the Mexican economy according to the likelihood of which their employment could be substituted with automation technologies. The first data source consist of the estimates proposed in Frey and Osborne (2017) regarding an occupation's probability of automation. These authors utilize detailed occupational data from O*NET, germane to define bottlenecks to the computerization of tasks, and classify occupations from the Standard Occupational Classification (SOC) according to the likelihood of which the tasks associated with an occupation can be automated. Frey and Osborne provide estimates for the probability of automation for 702 out of the 903 SOC occupations covered in O*NET. There are three important characteristics of the methodology underlying these estimates that are worth highlighting to better interpret the results that will follow. First, these estimates ***solely*** reflect the technological feasibility of automation. That is, whether the automation of a given occupation is technologically feasible. Second, the estimates are forward looking in the sense that they do not only consider whether an occupation can be automated now, but whether it is likely that advances in technology and artificial intelligence will allow for its automation in the future.[9] Third, even if O*NET is a US database, the identification of the tasks pertaining to an occupation does not apply uniquely to the United States. To the extent that the tasks involved in a specific occupation do not vary greatly across countries (i.e. the tasks that a worker needs to be able to perform to be a plumber or a lawyer are generally similar worldwide), the O*NET database is widely applicable. In the specific case of Mexico, we match the

[9]While the methodology outlined in Frey and Osborne (2017) is described as "forward looking" in the sense that it contemplates future possibilities for automation, the authors do not state an exact time frame. At times they suggest that they are contemplating a time frame of one decade, but this is not made explicit in their study.

occupations for which Frey and Osborne calculate a probability of automation with their Mexican counterparts using the SINCO (Sistema Nacional de Clasificación de Ocupaciones) from INEGI, which is built with the specific purpose of standardizing the classification of occupations and guaranteeing maximum comparability. This further alleviates the concern regarding the applicability of Frey and Osborne's probabilities to the Mexican context, at least for those occupations that can be matched. Figure 1 presents the top 10 and bottom 10 occupations according to the probability of automation as estimated by Frey and Osborne (2017).

Figure 1: Probability of automation: Top 10 vs. bottom 10 occupations



Note: The probabilities are taken from Frey and Osborne (2017).

The second source of data that we use is the Encuesta Nacional de Ocupación y Empleo (ENOE) collected by the Mexican statistical agency —Instituto Nacional de Estadística y Geografía (INEGI). ENOE is a nationally representative household survey of Mexican workers that includes data on the gender, age, education, employment status, income, occupation, geographical location, and sector of employment, among other worker characteristics. This survey is a rolling panel in which workers are tracked for at most five quarters before being dropped from the sample.[10] We work with data from the period 2013-2017, during which 466 occupations are identified out of the 702 occupations for which Frey and Osborne (2017)

[10]Being dropped from the sample does not preclude the possibility that a worker could be surveyed at a later round implementation of the survey.

provide an estimate of the probability of automation.[11] Our sample covers, on average, 58 percent of the total Mexican employment.[12]

Combining these two data sets allows for addressing the question of how automation may disrupt labor markets by analyzing how employment in Mexico is exposed to the threat of automation across gender, age, and education groups. Since ENOE is not designed to necessarily be representative of the distribution of employment across occupations, most of our baseline results are constructed considering the 'average' distribution of employment across occupations between 2016 and 2017, unless otherwise stated. In doing so we avoid omitting occupational categories that may appear unreported in a given year, due to their share in total employment. Our baseline results are the focus of the next section.

3 Employment at Risk in Mexico

In this section we provide an assessment of the risk faced by the Mexican labor market due to the potential automatability of employment. The estimates of Frey and Osborne (2017) represent our starting point for identifying which workers are potentially most exposed to the threat of automation. Since occupations are differentially exposed to the threat of automation, this heterogeneity across occupations, together with the distribution of Mexican workers across occupations, allows for analyzing the extent to which different groups of workers are exposed to the automation of their work.

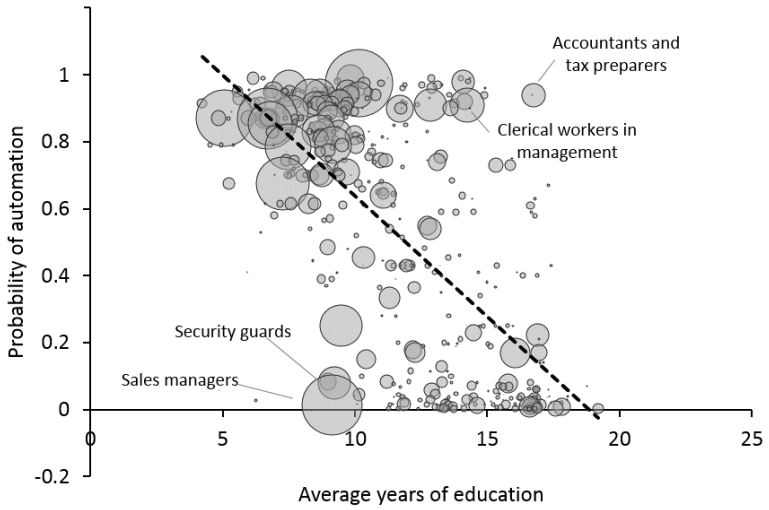
Before delving into the analysis, we highlight that an important point behind the methodology used by Frey and Osborne to arrive at their estimates is the assumption that a key determinant of the probability of automating an occupation is whether the tasks involved can be easily translated into a set of logical instructions. This assumption on the potential automatability of tasks is typically interpreted as implying that low skill workers are the most at risk of being replaced by automation technologies. Figure 2 presents the relationship between an occupation's probability of being automated and its skill intensity, proxied by the average years of schooling for workers found in that occupation in Mexico. It is easy to see that, on average, less skill-intensive occupations are more likely to be automated. However, this relationship is far from perfect. Occupations such as accountants and tax preparers employ workers that are relatively highly educated. Yet, their work is greatly exposed to the threat

[11] In some cases workers may report an occupation that cannot be properly mapped to the 702 occupations covered by Frey and Osborne or report their occupation as "other". In these instances it is impossible to determine the extent to which their employment may or may not be at risk of automation.

[12] This figure refers to employment in both the formal and informal sector.

of automation since many of the tasks involved can be easily programmed as a set of logical instructions to be performed by a computer. On the other hand, occupations such as security guards, sales managers or doulas, require workers with little schooling, but it is unlikely that these jobs will be automated. The reason being that it is improbable, at least for the near future, that automation will affect occupations that involve intangible skills (e.g. creativity, flexibility, adaptability), tacit knowledge regarding how tasks must be performed (i.e. difficult to codify), or where a key determinant of the quality of the output being produced relies on human interaction (see Autor, 2015, for further discussion of these issues).

Figure 2: Probability of automation and skill intensity by occupation

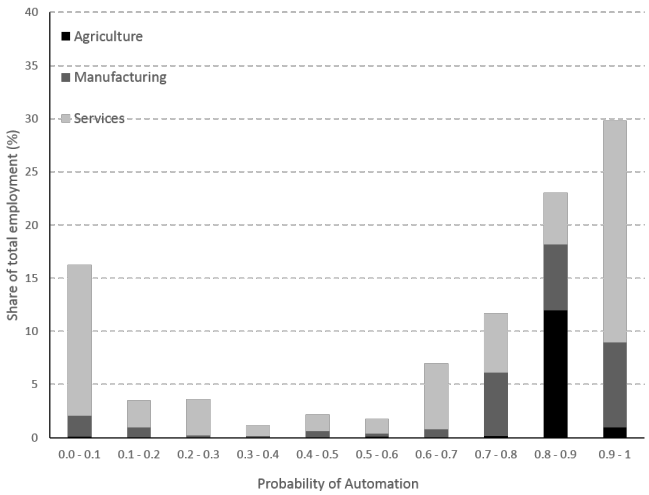


Note: Based on authors' calculations. The size of the bubbles is proportional to the average number of workers found in each occupation in Mexico between 2013 and 2017.

For the remainder of this section we adopt the share of workers at high risk of automation as our measure of the risk of disruption faced by the labor market due to advances in automation technologies. This follows Frey and Osborne (2017) who classify occupations according to their probability of automation into low-risk occupations (probability of automation less than or equal to 0.4), medium-risk occupations (probability of automation greater than 0.4 and less than or equal to 0.7), and high-risk occupations (probability of automation greater than 0.7). Figure 3 reports the distribution of Mexican employment across occupational categories that are grouped according to their probability of automation. It is easy to see that employment is mostly concentrated in occupations at low and high risk of automation, with medium-risk occupations commanding a very small share of total employment. It can also be verified that, while employment in both the service and manufacturing sector is distributed across

the entire spectrum of automation risk, agricultural employment is entirely accounted for by occupations at high risk of automation. Based on this distribution of employment we estimate that nearly 65 percent of Mexican employment is at high risk of being automated.[13]. This contrasts with the 44 percent of employment at high risk of automation that we estimate for the United States.[14] This stark difference is likely due to the fact that the United States has a higher share of employment in skill-intensive and service sector occupations which are typically less exposed to the threat of automation.

Figure 3: Distribution of Mexican employment by degree of automatability



Note: Based on authors' calculations.

While the 65 percent of employment that we estimate to be at high risk of automation in the Mexican economy is of interest in itself, policy discussions surrounding automation often focus on the potential distributional implications associated with this phenomenon. As such, we disaggregate our estimate across demographic groups to better assess whether there are groups of workers who are particularly exposed to the threat of automation. Disaggregating by gender, we find that men are more exposed to automation since 69 percent of men are at high risk of automation; for women this number is 59 percent. This again contrasts with the figures obtained for the United States, for which we find that it is women rather than men who are more exposed to the threat of automation with the employment of 43 percent of women

[13]This result is in line with the figures reported in Minian and Martínez Monroy (2018) who find that 63 percent of the total employment and 64.5 percent of the manufacturing employment in Mexico are at high risk of being automated.

[14]Frey and Osborne (2017) originally estimated this number to be 47 percent. We update their estimate based on the Current Population Survey for 2017.

being at high risk versus 35 percent for men.[15] This is explained by the fact that female labor participation in Mexico is lower and a large share of women are employed in occupations involving skills that are less susceptible to the risk of automation. Considering an average over the past three years (2016Q4-2019Q3), the top 5 occupations with the highest female employment are: domestic workers; sales employees, dispatchers and sales clerks; merchants in establishments, secretaries, cleaning workers (except in hotels and restaurants). These 5 occupations alone command about 30 percent of the total female employment over the same period.

Figure 4 further disaggregates our estimates by age groups and educational attainment. The top panel of Figure 4 shows that younger workers tend to be more exposed to the automation of their employment, and that for all age groups women are less exposed than men. The bottom panel of Figure 4 shows that the share of employment at high risk of automation is negatively and strongly associated with educational attainment. Specifically, the marginal decrease in exposure to the threat of automation is substantial as more human capital is accumulated past high school. That is, the threat of automation drops significantly as one moves from workers with a high school degree to those with a college education, and, again, as one moves from workers with a college degree to those with graduate studies. In contrast to the top panel of Figure 4, it is not true that women in all educational groups are less exposed than men. Females with a high school or a college education are marginally more exposed to the automation of their employment than men.

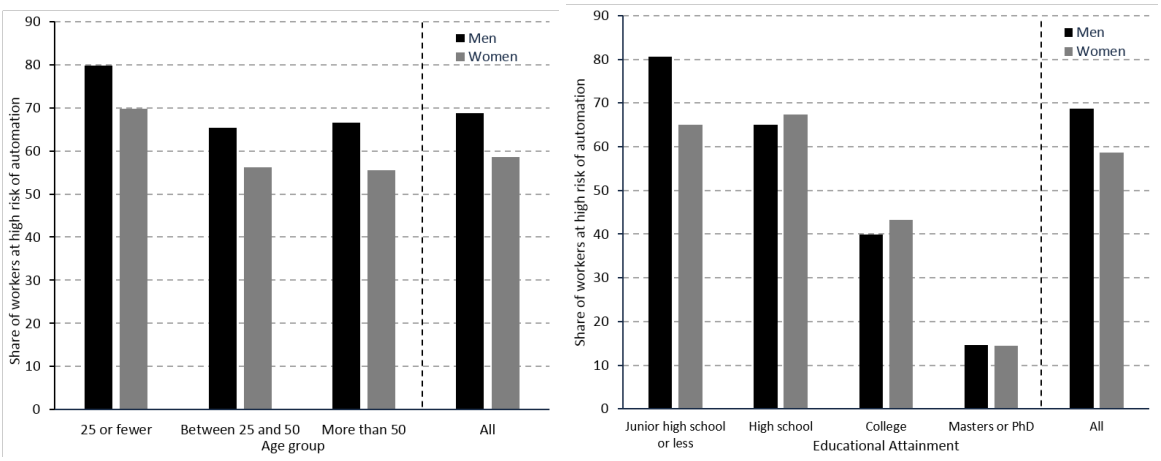
Finally, Table 1 presents the share of workers at high risk of automation dissecting by gender, age, and conditioning on educational attainment. As suggested by Figure 4, Table 1 confirms that young, poorly educated males are the demographic group most at risk of being replaced by automation technologies.[16] Table 1 also identifies that it is only in 5 of the 12 age/education groups that women are more exposed to the threat of automation. These groups correspond to female workers aged 25 to 50 and older than 50 with a high school or college education, and female workers aged 25 or younger with graduate studies.

Our results show that: *(i)* young workers are particularly exposed to the automation of their occupations, and *(ii)* whether workers are actually forward-looking or not in this dimension, human capital accumulation operates as a particularly effective self-insurance mechanism for workers to face a lower risk of automation. The adjustment of labor markets to the threat

[15]These estimates are based on the Current Population Survey for 2017. The finding that women are more exposed to automation than men also holds true for Mexico if we were to look only at employment in the formal sector.

[16]Poorly educated young workers may have, however, the chance to improve upon their vulnerability to the threat of automation by acquiring more education.

Figure 4: Risk of automation by age group and educational attainment



Note: Based on authors' calculations.

of automation will depend, in part, to the extent to which new cohorts of workers entering the labor force are already internalizing the risk of automation that different occupations are exposed to. Thus, the threat of automation could potentially affect the occupational choices of new workers entering the labor force and/or the educational choices of prospective workers. To the extent that these choices internalize the changing nature of jobs and the future direction of technological progress, adjustments in labor markets could occur more smoothly than they otherwise would. For the remainder of this section we focus on workers aged 25 or younger, and analyze whether there is any evidence that could suggest that new cohorts of workers are adjusting their behavior in response to the changing nature of employment and the prospective path of technological change.

Figure 5 presents the distribution of workers aged 25 years or less across low, medium, and high risk of automation occupations for each year between 2013 and 2017.[17] As shown, the distribution of young workers across occupations that differ in their likelihood of being automated has been remarkably stable in Mexico during the period considered. Additionally, nearly half of all young workers are employed in an occupation that has a high probability of being automated, with only roughly 10 percent of young workers being employed in an occupation with a low probability of automation. Figure 5 suggests that any occupational switching that these young workers may be doing is limited, for the most part, to switching between occupations that belong to the same broad risk category (i.e. any occupational switching among young workers is mostly *within* risk categories, not *across* risk categories).

[17]Since each year provides the distribution of workers that in that year where aged 25 or less, Figure 5 does not preclude the possibility that the same worker is present in the sample in various years.

Table 1: Risk of automation across different demographic groups

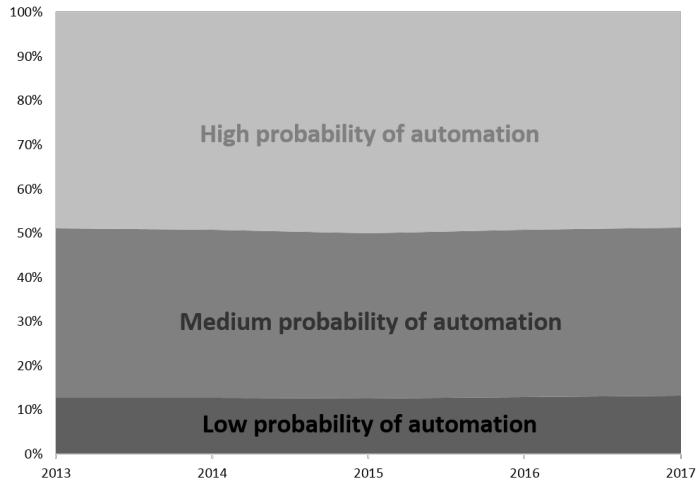
Men					
Age	**Education**				
	Junior high school or less	High school	College	Graduate studies	***Total***
25 or younger	81.7	77.6	56.1	22.3	79.8
Between 25 and 50	79.8	60.8	37.3	16.0	65.4
More than 50	77.6	50.9	35.2	11.5	66.5
Total	80.6	65.1	39.8	14.7	68.7
Women					
Age	**Education**				
	Junior high school or less	High school	College	Graduate studies	***Total***
25 or younger	76.7	74.9	50.8	30.9	69.7
Between 25 and 50	64.4	65.0	41.4	15.6	56.3
More than 50	60.6	52.7	43.5	8.6	55.5
Total	65.1	67.3	43.3	14.5	58.6

Notes: Based on authors' calculations. Each cell reports the share of workers at high risk of automation amongst those workers who pertain to each specific cell.

In 2015 the INEGI conducted a special module of ENOE —the Módulo de Trayectorias Laborales (MOTRAL)— that focused on the labor market trajectories of respondents. For our purpose, a key piece of information that is available from MOTRAL, but not from ENOE, is a worker's occupation of first employment and the year in which they entered the labor market for the first time. This allows for analyzing whether different cohorts of young workers are making different occupational choices upon entering the labor market for the first time. Figure 6 shows the distribution of each cohort of new workers across low, medium, and high risk of automation occupations for cohorts of young workers entering the labor market for the first time between 2000 and 2015.[18] Figure 6 clearly shows that the distribution of entering workers across the three categories of occupations under consideration has remained fairly stable from 2008 onwards. In particular, approximately 40 percent of young workers entering the labor force do so by finding employment in occupations at high risk of automation, while roughly 27 percent find their first employment in occupations at low risk of automation. Similarly to Figure 5, Figure 6 also suggests that the threat of automation has had a limited impact, if at all, on the labor market choices of workers as new cohorts of young workers entering the labor market are not significantly modifying their choice of occupation of first

[18]The category "other" corresponds to those workers who entered the labor market in an occupation that we cannot map into one of the occupations for which Frey and Osborne (2017) provide estimates for the likelihood of automation or whenever a workers self-reported occupation is "other".

Figure 5: Employment distribution of workers aged 25 or less



Note: Based on authors' calculations.

employment relative to previous cohorts, at least during the 2008-2015 period.[19]

Finally, we analyze the sorting of young workers across formal and informal employment given the prominence of informal employment in the Mexican economy. We estimate the following linear regression

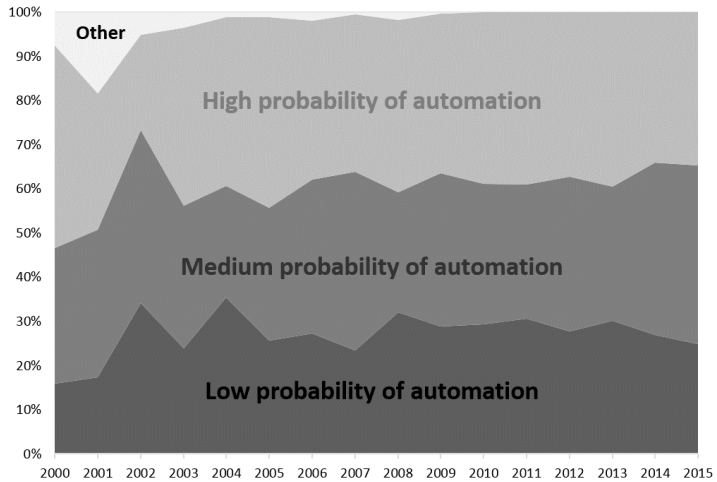
$$\begin{aligned} \ln\left(p_{jt}^{f}\right) - \ln\left(p_{jt}^{inf}\right) = \; & \alpha + \lambda_j + D_j \times \Delta GDP_{t-1} + \delta_0\left(w_{jt}^{f} - w_{jt}^{inf}\right) \\ & + \delta_1 \sigma_{jt} \times \left(w_{jt}^{f} - w_{jt}^{inf}\right) + \delta_2 q_j \times \left(w_{jt}^{f} - w_{jt}^{inf}\right) + \varepsilon_{jt} \end{aligned} \tag{3.1}$$

where the dependent variable is the difference between the proportion of young workers choosing occupation j in the formal sector $\left(p_{jt}^{f}\right)$ and the proportion of young workers choosing the same occupation in the informal sector $\left(p_{jt}^{inf}\right)$. The dependent variable is explained by the wage differential between formality and informality $\left(w_{jt}^{f} - w_{jt}^{inf}\right)$ in the same occupation j, and its interaction with wage volatility $\left(\sigma_{jt}\right)$ to control for the "riskiness" of income across occupations, and its interaction with the probability of automation $\left(q_j\right)$. We also include occupation fixed effects and a term controlling for the business cycle that can potentially affect occupations asymmetrically.[20] Since the dependent variable is the result of demand

[19]During the 2001-2006 period we see some action along this margin. However, this is likely due to China entering the WTO in 2001, which represented a significant shock to Mexican labor markets and induced important adjustments in the sectoral composition of economic activity in Mexico. See, for example, Chiquiar, Covarrubias, and Salcedo (2017).

[20]Leyva and Urrutia (2018) discuss how the share of informal employment in total employment varies along the cycle. One of their main findings is that the share of workers in the informal sector in Mexico is countercyclical

Figure 6: Distribution of new cohorts of young workers across occupations



Note: Based on authors' calculations. Each year corresponds to the distribution of employment for workers, aged 25 or less, who entered the labor market for the first time in that year.

and supply forces, our results will not capture the causal effect of automation on the sorting of workers. However, we argue that our regression results are still useful as a mechanism to explore patterns in the data.

The estimates of equation (3.1) are reported in Table 2. They suggest that for young workers the wage premium that employment in occupation j offers in the formal vs. informal sector is positively and significantly associated with the sorting pattern of workers across formal and informal employment. The results in columns (2) and (3) indicate that the earnings risk associated with each occupation, captured by the wage volatility for the occupation in the formal sector, mutes the effect that the wage premium has on the sorting pattern of workers and this effect is statistically significant. However, the threat of automation faced by an occupation, captured by that occupation's likelihood of being automated, does not significantly affect how workers sort between formal and informal employment within an occupation.

As previously noted, occupational choices are not the only margin of adjustment available to new cohorts of workers that face the risk of automation. Educational choices can also represent an important margin along which individuals can internalize the changing nature of the labor market and prepare for the labor demand that they might face upon entering the labor force. We begin by analyzing how the exposure to automation may have changed between 2013 and 2017 for workers with a given educational background. Exposure to automation for

in the presence of shocks to the international interest rate. This suggests that, due to the lack of social safety nets in Mexico, informal employment acts as a buffer against earnings shocks in the formal labor market.

Table 2: Sorting of young workers across formal and informal employment

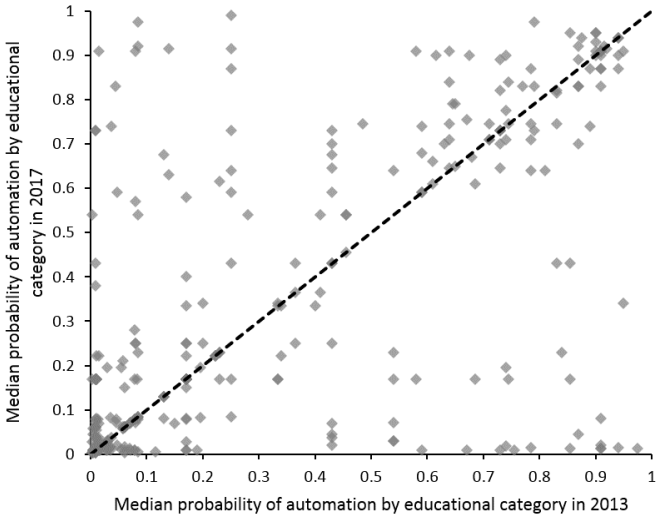
	(1)	*(2)*	*(3)*
$\left(w_{jt}^{f} - w_{jt}^{inf}\right)$	0.078^{***}	0.076^{**}	0.410^{***}
	(0.027)	(0.038)	(0.196)
$q_j \times \left(w_{jt}^{f} - w_{jt}^{inf}\right)$		−0.002	0.0002
		(0.015)	(0.017)
$\sigma_{jt} \times \left(w_{jt}^{f} - w_{jt}^{inf}\right)$			-0.044^{*}
Constant	1.15^{***}	0.127	14.342^{*}
	(0.326)	(0.445)	(5.955)
Observations	6,555	6,483	5,814
Adjusted R^2	0.82	0.82	0.85

Note: The sample includes information at the occupational level for young individuals between 20 and 30 years of age. The observations are at the quarterly frequency for the period 2013-2017. All the specifications include an occupation fixed effect, as well as controls for the business cycle specified as an interaction between the past quarter GDP growth and an occupation-specific dummy variable. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Standard errors are reported in parenthesis.

an educational category can change between years if the occupational distribution of workers with that educational background changes across years. Figure 7 plots the median probability of automation across workers within a given educational category for both 2013 and 2017, at the most disaggregated level of educational categories allowed by ENOE. For 60 percent of the educational categories, the median probability of automation decreased between 2013 and 2017. This suggests that the majority of educational categories incurred in a compositional change such that the distribution of workers with a given educational background shifted, on average, towards occupations with a lower risk of automation. Notice, however, that there are many educational categories in which the median probability of automation for workers within that category significantly increased between 2013 and 2017.

A natural question to ask in this context is whether certain types of educational backgrounds that are more exposed to the risk of automation are being shunned in favor of a process of human capital accumulation that is more favorable to the likely labor market challenges that workers will face given the penetration of automation technologies in the workplace. Figure 8 relates the median probability of automation for workers found in a given educational category in 2013 to the change of the share of workers found in each of these categories between 2013 and 2017. The negative relationship depicted in Figure 8 seems to indicate that Mexican workers have shifted away from educational backgrounds that were associated with occupations at high risk of exposures to the threat of automation, in favor

Figure 7: Change in exposure to automation across education categories

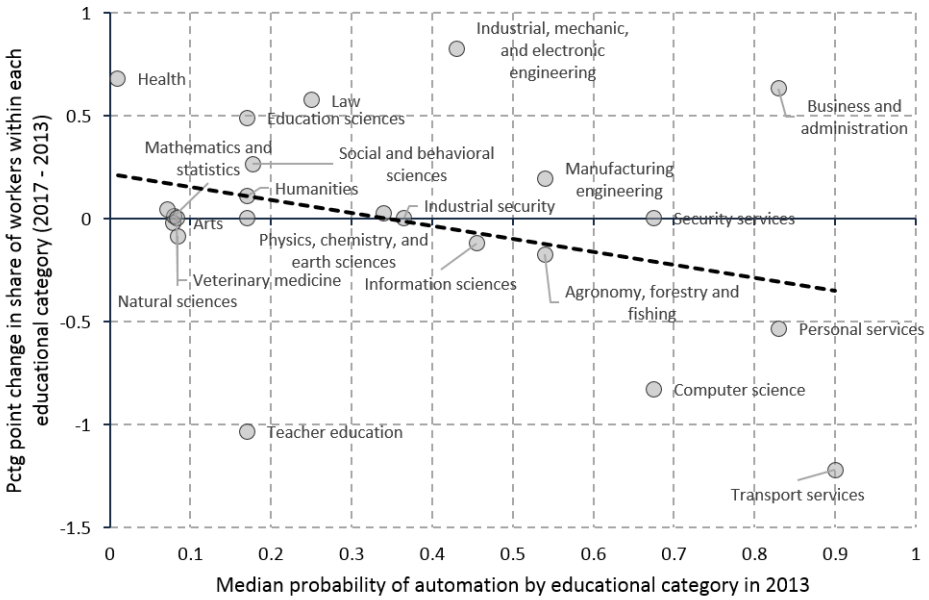


Note: Based on authors' calculations. Education categories correspond to 4 digit level categories reported in ENOE.

of educational backgrounds that in 2013 were associated with occupations less exposed to this threat. Nonetheless, it is important to note that this negative correlation does not control for other factors that may have contributed to this shift across education categories, such as human capital policies and changes in the relative labor demand for certain types of workers.

The evidence presented in Figures 5 and 6 and in Table 2 suggests no impact, or a very limited one, of the threat of automation on the labor market choices (outcomes) of young Mexican workers. Regarding educational choices, Figures 7 and 8 seem to indicate that, to some extent, Mexican workers have favored the accumulation of human capital that is less substitutable with automation technologies in lieu of certain educational backgrounds that have been associated with a high degree of exposure to the threat of automation. However, these observed patterns could be driven by other factors (e.g. human capital policies or changes in relative labor demands) that we are not controlling for rather than being a labor supply response associated with the threat of automation being internalized by prospective workers. Overall, this evidence does not lend strong support to the hypothesis that young and prospective workers are responding through their educational and occupational choices to the threat that the adoption of automation technologies may pose for certain types of employment. The lack of evidence that we find in this regard would be consistent with either a limited adoption of automation technologies in the Mexican economy, such that workers do not yet perceive it as a credible threat to their employment, and/or the subjective expectations

Figure 8: Change in educational backgrounds and probability of automation



Note: Based on authors' calculations. Education categories are grouped at the 2 digit level reported in ENOE. The negative relationship depicted in this graph corresponds to a correlation of -0.32 between the two variables in question.

that workers hold regarding the likelihood of automation of their employment being poorly approximated by the estimates of Frey and Osborne (2017).[21]

An important reason why workers' subjective expectations regarding the likelihood of different types of employment being automated can be at odds with the estimates of Frey and Osborne is that these authors only consider the ***technical feasibility*** of automating tasks. Conversely, workers may incorporate into their subjective expectations the ***economic incentives*** that firms have for adopting these technologies. This brings up an important limitation behind the type of calculations that have been presented so far and that are also found elsewhere in the literature and policy discussion (see, for example Frey & Osborne, 2017; Manyika et al.,

[21] Kugler, Kugler, and Rodrigo (2018) present evidence from the International Federation of Robotics regarding the accumulation of industrial robots in Latin American countries. For the case of Mexico they show that up to 2016, the last year in their data, the penetration of industrial robots in the Mexican economy was mostly accounted for by the automotive sector. Between 2011 and 2016 the stock of industrial robots (per thousand of workers) grew by 97 percent in the automotive sector and by the end of the period the stock of industrial robots (per thousand of workers) in the automotive sector was six times larger than the stock in the plastic and chemicals manufacturing sector, the sector with the second highest stock of industrial robots by 2016. Furthermore, in every sector other than the automotive sector, the stock of industrial robots (per thousand of workers) was relatively flat between 2011 and 2016.

2017; Nedelkoska & Quintini, 2018).[22] Specifically, these calculations do not account for the economic incentives that exist in each economy to incorporate automation technologies into the productive structure of the economy. A deeper discussion of this issue is the focus of the next section.

4 What about the Economic Incentives to Automate?

In the previous section we used the occupational distribution of employment contained in ENOE together with the estimates of Frey and Osborne (2017) to provide an initial assessment of the risks that the automation of employment may pose for the Mexican labor market. Some of the key takeaways from the analysis were that: *(i)* 65 percent of total employment is at high risk of being automated; *(ii)* in the aggregate, the employment of men is more exposed to the risk of automation than that of women; and *(iii)* human capital accumulation, through the occupational choices that it induces on workers, can serve as an important mechanism for workers to protect themselves from the threat of automation. These calculations certainly provide an interesting benchmark from which to start a discussion regarding the possible impacts of automation on labor markets and the economy, and possible policy responses. Even so, it is important to stress that there are significant limitations underlying these calculations and, as such, they should be interpreted with caution to avoid overstating (or understating) the impact that automation technologies may have on labor markets in both advanced and emerging economies.

The first problem that any researcher or policy-maker wishing to understand the impact of automation technologies on the economy is confronted with is the lack of relevant data that can be useful for addressing the various questions that arise in such a broad issue. Two significant limitations should be noted. First, the lack of firm-level data regarding investments in IT and industrial robots that could shed light on the ways in which firms re-organize production when they incorporate automation technologies into their operations. This would be particularly important to gain a microeconomic understanding of which tasks and occupations can be substituted/complemented by automation technologies and how these patterns of substitutions and complementarities shape firm-level productivity (see Seamans & Raj, 2018). Second, the lack of more nuanced or disaggregated occupational data that can provide sharper distinctions between the different types of tasks that workers perform in the

[22] On April 24th, 2018 *The Economist* published an article titled "A study finds nearly half of jobs are vulnerable to automation". The numbers reported in that article are calculated in a similar spirit to the numbers reported in this section.

workplace. While the SOC occupations cover over 900 different types of employment, these occupations can still be broad enough that there is immense heterogeneity in the types of work performed by different workers within the same occupation. For example, both a Ph.D. economist and a bachelor degree economist may be classified within the same occupation as "economist", yet the nature of the tasks they perform can differ sharply. That is, standard labor data collected across the world tend to focus on aggregate statistics that lack the granularity of the specifics that distinguish different types of work. Given that technology directly impacts the demand for precise skills rather than the demand for occupations as a whole, this lack of detail could imply that the probability of automation for different kinds of workers within the same occupation is not necessarily the same. In terms of the calculations of section 3, this lack of nuance in occupational data can lead to overstate the share of employment that is at high risk of being automated.[23]

A recent paper by Nedelkoska and Quintini (2018) takes an important step in the direction of obtaining estimates of the probability of automation of work at a more disaggregated level than the estimates of Frey and Osborne. Indeed, they find that, once a more nuanced approach regarding the nature of work and the possibilities of automation is adopted, the type of calculations presented in section 3 tend to overstate the magnitude of the problem that automation can represent for incumbent workers in the labor market. Despite the valuable effort in terms of obtaining more refined estimates of the share of employment that is at high risk of automation, an important limitation of their approach, which is shared with the estimates of section 3 here, is that these estimates do not incorporate the ***economics of automation***. That is, most current estimates of the threat that automation may pose for labor markets do not incorporate the incentives that employers face to adopt automation technologies, nor the general equilibrium effects that the displacement of workers will induce in the economy.

In the remainder of this section we highlight some issues that we consider particularly relevant to understand the economic incentives to automate in Mexico and other emerging markets with a high degree of trade openness. In particular, in the short run the threat of automation may be diminished in emerging markets given three relevant factors. First, low wages, relative to the cost of new technologies, reduce the profitability of introducing automation technologies into the workplace. Second, low human capital may pose an obstacle to the adoption of new technologies. Third, the prevalence of informality and of small

[23]See Frank et al. (2019) for a more detailed discussion regarding possible ways in which data collection can be improved with the goal of gaining a better understanding of the impact of AI on employment and the demand (and supply) of workplace skills.

and medium-sized enterprises in the formal sector, that will potentially adopt this form of technological change at a slower pace, may limit the adoption of automation technologies. In what follows we advance a series of considerations and illustrative exercises that we believe to be important to further our understanding of the extent to which automation poses a threat to employment in the Mexican economy. In particular, we emphasize the role that informal sector employment, wages, and the offshorability of occupations may play in shaping technology adoption decisions and thus, ultimately, the pace at which automation will penetrate the economy's productive structure.

4.1 Informality in the Labor Market

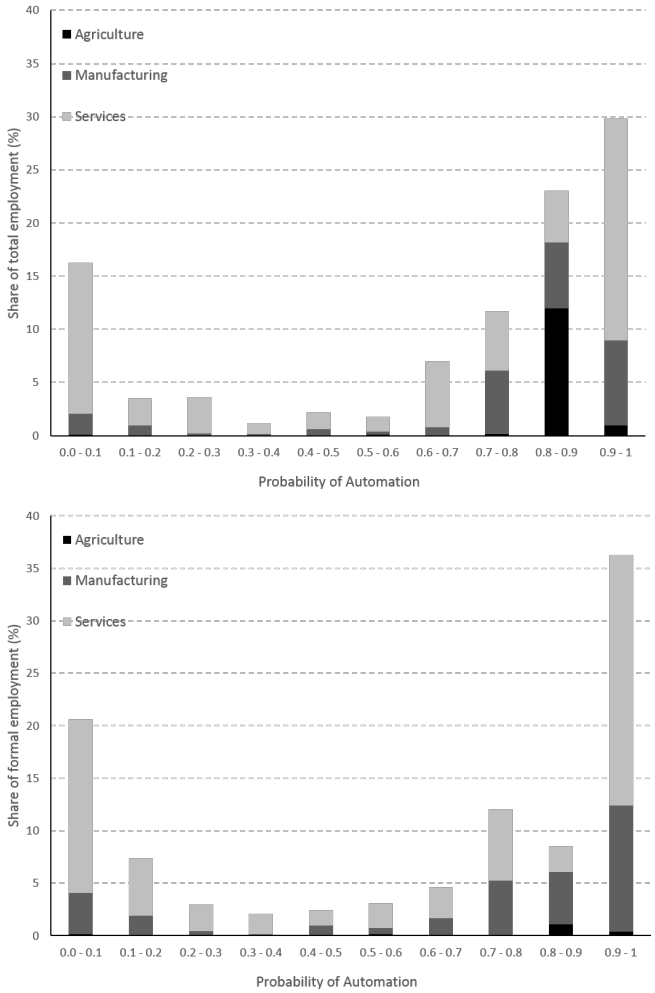
A salient feature of the Mexican labor market is the prevalence of informal labor relationships and the abundance of small and medium-sized enterprises in the formal sector.[24] Given that self-employment and small establishments are typical of the informal sector, it is possible that automation will have a differential effect across formal and informal employment. Figure 9 reports the distribution of Mexican employment across occupational categories that are grouped according to their probability of automation, distinguishing total from formal sector employment. Informal employment is particularly prevalent in agriculture, where employment is also highly concentrated in activities that are at a high risk of being automated. It is natural to wonder whether agricultural workers are truly so highly exposed to the threat of automation or the fact that labor relationships in this sector are predominantly informal does play any role in the effective threat that they face.

Similarly to the previous section, we study the share of workers whose employment is at high risk of being automated across formal and informal employment. Figure 10 and Table 3 report the share of employment at high risk of automation distinguishing by gender and type of employment. We find that 69 percent of informal employment is at high risk of automation, which contrasts with the 57 percent that we encounter in the formal sector. Differences in exposure across formal and informal employment are most pronounced for men. In fact, the share of male workers at high risk of being displaced because of automation is 20 percentage points higher in the informal sector relative to the formal sector.

The difference in exposure to the threat of automation across formal and informal em-

[24]Informal sector workers are defined as those without access to social security benefits. According to figures reported by INEGI, the quarterly rate of informality during the period 2005-2018 hovered between 56 and 59 percent of total employment. Regarding small and medium-sized enterprises, Levi-Algazi et al. (2018) estimates that, based on the 2013 economic census published by INEGI, 94 percent of the economy's productive units are establishments with 5 workers or less, and only 0.4 percent of the establishments employ more than 50 workers.

Figure 9: Distribution of employment by degree of automatability: total vs. formal sector

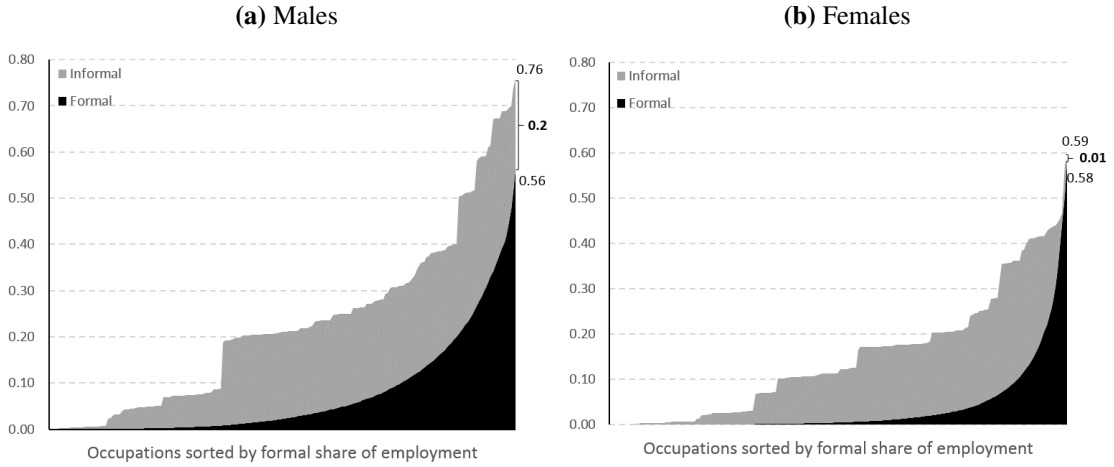


Note: Based on authors' calculations.

ployment that we document for Mexico appears counterintuitive. The informal sector is characterized by self-employment and employment in micro establishments that are typically credit constrained and less technologically advanced than formal sector establishments. Thus, it is hard to believe and justify that automation will pose a greater threat to employment in the informal sector than in the formal sector. We interpret our finding as evidence of the necessity of incorporating the technological possibilities ***and*** economic incentives for the adoption of automation technologies into any analysis that seeks to quantify the magnitude of the threat posed by automation.

As a first approximation, we consider that it is reasonable to assume that the informal sector has either no economic incentive or no possibility to adopt automation technologies.

Figure 10: Distribution of employment across occupations at high risk of automation: formal vs. informal sector



Note: Based on authors' calculations. The graphs depict cumulative employment shares. The occupations at high risk of being automated depicted in these graphs have been ordered by their share of employment in the formal sector (that is why the black bars are depicted in a smooth way). This ordering has been done separately by gender.

Table 3: Share of employment at high risk of automation

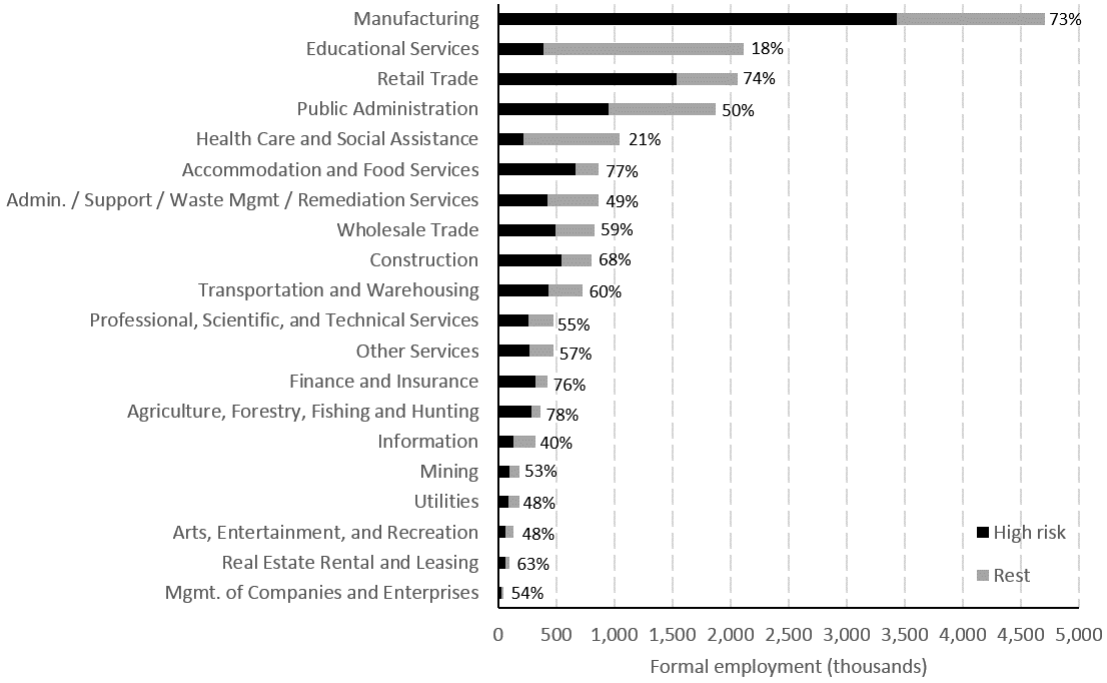
	Formal	Informal	***Total***
Male	0.56	0.76	0.69
Female	0.58	0.59	0.65
Total	0.57	0.69	0.65

Note: Based on authors' calculations. Numbers are reported in percentages.

This assumption alone changes our risk assessment importantly: rather than 65 percent of total employment being at high risk of automation, we would estimate that 57 percent of formal sector employment is at high risk of being automated. In turn, this would imply that roughly 25 percent of total employment in Mexico is at high risk of being automated.[25] Also notice that, once we exclude informal employment, it is women rather than men who are more exposed to the threat of automation (see Figure 10), consistent with findings for other countries (see, for example, Frey & Osborne, 2017). Narrowing our focus on employment in the formal sector, in what follows we revisit the differential impact that automation may have across demographic groups and industries.

[25]This is because the formal sector represented between 41 and 44 percent of the total employment during the period 2008-2018 according to INEGI.

Figure 11: Sectoral heterogeneity in the share of formal employment at high risk of being automated



Note: Based on authors' calculations.

Figure 11 reports the share of formal sector workers at high risk of automation across sectors of economic activity.[26] Figure 11 shows that formal employment in the manufacturing sector is particularly exposed to the threat of automation. From a regional perspective, this implies that central and northern states are more exposed to the threat of automation of formal sector jobs, given that these states concentrate a large share of total manufacturing activity in Mexico. In fact, once we focus on formal employment, there is a positive correlation between a state's share of employment at high risk of automation and a state's real GDP per capita.[27] This likely reflects the fact that in more economically developed states the service and manufacturing sectors command a large share of economic activity and these sectors also employ a large share of workers whose employment is highly susceptible to automation.

Two findings of section 3 were that educational attainment appeared to act as a particularly

[26]For a discussion regarding the threat of automation from a regional perspective see Box 2 in Banco de México's July-September 2018 Report on Regional Economies available at: http://www.banxico.org.mx/publicaciones-y-prensa/reportes-sobre-las-economias-regionales/reportes-economias-regionales.html.

[27]We take the state's average real GDP per capita (excluding the oil sector) for the period 2013-2016 as our proxy for a state's level of development.

successful form of self-insurance against the threat of automation, independently on whether workers are forward-looking when accumulating human capital, and that younger workers were those more exposed to the automatability of their occupations. We explore these results more rigorously within the context of formal sector employment by running a multinomial logit regression for the outcome variables *employed in medium-risk occupation* and *employed in high-risk occupation*, controlling for a set of socio-economic characteristics of workers. In particular, we model workers occupational choices as follows. Each occupation has a probability of automation, hence choosing an occupation implies that the worker will be at low ($0 \leq p < 0.3$), medium ($0.3 \leq p < 0.7$), or high risk ($p \geq 0.7$) of being displaced because of automation. The choice of an occupation depends on individual characteristics such as, gender, age group, education, wage, family size, and whether the individual belongs to a high income family and is the head of the household.

The base category in our specification is the low risk of automation and all the results need to be interpreted and understood with respect to it. That is, the estimated coefficients represent the marginal effect that factors such as gender, educational attainment, and age have on the probability of being employed in a medium- or high-risk occupation ***relative*** to a low-risk occupation. So, for example, for the medium risk category the coefficient associated with the dummy variable female is negative and significant. This means that being a woman decreases the probability of choosing an occupation at medium risk of being automated with respect to the probability of choosing an occupation at low risk of automation. Conversely, for the high risk category the coefficient associated with the dummy variable female is positive and significant, implying that being a woman increases the probability of choosing an occupation at high risk, relative to the probability of choosing an occupation at low risk.

When dealing with independent categorical variables that have more than two categories, the interpretation of the results is more complex. All the results continue to be relative to the outcome base category (in this case the low risk of automation category), but the coefficients associated with the different categories of the explanatory variables measure how different levels of the variable[28] affect the probability of an individual opting for a specific choice versus the probability of opting for the base choice. The results of our estimation are reported in Table 4.

[28]In this instance different levels of the variable means different than the omitted category. For educational attainment the omitted category is "less than high school" and for age the omitted category is "less than 25".

Table 4: Effect of sociodemographic characteristics on the probability of being employed in occupations at high risk of automation

	All sectors		Agriculture		Manufacturing		Services	
	Med/Low	*High/Low*	*Med/Low*	*High/Low*	*Med/Low*	*High/Low*	*Med/Low*	*High/Low*
Female	−0.316***	0.311***	−0.159	0.0337	−1.126***	−0.0321**	−0.416***	0.146***
(= 1 if female)	(0.00908)	(0.00621)	(0.101)	(0.0786)	(0.0231)	(0.0136)	(0.00936)	(0.00621)
Household head	−0.0562***	−0.100***	−0.0751	−0.0906	−0.0852***	−0.117***	0.0363***	−0.0178***
(= 1 if household head)	(0.00926)	(0.00648)	(0.0857)	(0.0687)	(0.0194)	(0.0136)	(0.00998)	(0.00689)
Household size	−0.0178***	−0.0000368	0.115***	−0.00486	−0.0358***	0.0109*	−0.0247***	0.00481
	(0.00426)	(0.00296)	(0.0330)	(0.0265)	(0.00871)	(0.00601)	(0.00470)	(0.00324)
High household income	−0.128***	−0.141***	−0.214*	0.431***	−0.130***	−0.0975***	−0.0800***	−0.130***
(= 1 if income $\geq$ 15, 000)	(0.0109)	(0.00757)	(0.109)	(0.0842)	(0.0241)	(0.0164)	(0.0116)	(0.00793)
ln(median wage)	−0.346***	−0.682***	0.0156	−0.917***	−0.534***	−0.964***	−0.0786***	−0.515***
	(0.00863)	(0.00628)	(0.0531)	(0.0416)	(0.0188)	(0.0137)	(0.00925)	(0.00655)
Education								
High school	0.257***	−0.166***	0.00496	−0.473***	0.0537***	−0.559***	0.246***	−0.0641***
	(0.00982)	(0.00727)	(0.0901)	(0.0740)	(0.0191)	(0.0136)	(0.0107)	(0.00795)
College	−0.782***	−1.167***	−0.769***	−1.495***	−0.577***	−1.648***	−1.041***	−1.205***
	(0.0103)	(0.00675)	(0.0816)	(0.0601)	(0.0193)	(0.0131)	(0.0107)	(0.00703)
Masters/Ph.D.	−1.534***	−1.937***	−0.895***	−2.053***	−1.094***	−1.858***	−2.146***	−2.380***
	(0.0286)	(0.0180)	(0.297)	(0.238)	(0.0788)	(0.0497)	(0.0288)	(0.0185)
Age group								
26−40	−0.316***	−0.381***	−0.449***	−0.504***	−0.116***	−0.189***	−0.338***	−0.499***
	(0.0112)	(0.00799)	(0.109)	(0.0910)	(0.0216)	(0.0149)	(0.0125)	(0.00892)
41−55	−0.579***	−0.509***	−0.707***	−0.610***	−0.133***	−0.184***	−0.696***	−0.741***
	(0.0125)	(0.00876)	(0.114)	(0.0949)	(0.0247)	(0.0171)	(0.0137)	(0.00958)
56−70	−1.051***	−0.895***	−1.231***	−0.780***	−0.481***	−0.480***	−1.102***	−1.089***
	(0.0176)	(0.0119)	(0.136)	(0.107)	(0.0388)	(0.0265)	(0.0189)	(0.0128)
71 and above	−1.767***	−1.794***	−1.518***	−0.423**	−1.402***	−1.440***	−1.522***	−1.936***
	(0.0465)	(0.0292)	(0.251)	(0.168)	(0.149)	(0.0910)	(0.0485)	(0.0344)
Constant	3.867***	8.980***	0.0984	10.76***	4.655***	10.48***	0.701***	5.824***
	(0.124)	(0.0884)	(0.516)	(0.404)	(0.168)	(0.123)	(0.0851)	(0.0601)
State fixed effects	No		Yes		Yes		Yes	
Time fixed effects	No		Yes		Yes		Yes	
State and time fixed effects	Yes		No		No		No	
Industry fixed effects	Yes		No		No		No	
Observations	1,125,358		29,753		324,257		770,719	
Pseudo R^2	0.195		0.113		0.122		0.098	

Note: The sample includes information at the occupational level for individuals employed in the formal sector. The observations are at the quarterly frequency for the period 2013-2017. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$ and $^{***}p < 0.01$. Standard errors are reported in parenthesis.

For both choice categories —medium and high risk— the negative and significant coefficients associated with all age groups indicate that belonging to an increasingly higher age group (higher than the lowest age group) decreases the relative probability to select an occupation at medium and high risk of automation. That is, for an older individual the relative probability of choosing an occupation at medium and high risk (relative to the probability of choosing an occupation at low risk) is lower than the same relative probability for a young individual. Moreover, as the coefficients associated with the age group are all negative and monotonically increasing, the higher the age group (the older the individual), the stronger the effect of age on the relative probability. The same applies to educational attainment. The negative and significant coefficients associated with higher educational attainments mean that for an individual with more education the relative probability of selecting an occupation at medium and high risk of automation (relative to the probability of selecting an occupation at low risk) is lower than the same relative probability for an individual who has not completed high school (which is the base education category). Since for education the coefficients are also monotonically increasing, this means that the effect of education is stronger as individuals acquire increasingly higher levels of education.

In sum, the findings of section 3 are confirmed in this more sophisticated exercise: educational attainment is related with a diminished exposure to the threat of automation, and the magnitude of this effect gets stronger as agents accumulate more human capital. Also, younger workers are more exposed to the threat of automation. These patterns are consistent across all broadly-defined sectors of economic activity (i.e. agriculture, manufacturing, and services).

The robustness and statistical significance of these results suggest the possibility that one of the possible returns to human capital accumulation is a kind of employment protection (in this case against automation) that may result from higher education leading to, for example, occupational choices in which intangible skills (i.e. creativity, flexibility, adaptability, etc.) that are in short supply in the labor market are used intensively. These results just add to the myriad of reasons why human capital policies are of paramount importance in emerging market economies. The interpretation of the results regarding the effect of age on the probability of employment in occupations at high risk of automation is less direct, but plausibly indicates that these are driven by upgrading to more skill-intensive occupations, or occupations that are intensive in the use of social skills and/or tacit knowledge, along the life-cycle as workers gain more labor market experience.

We conclude this sub-section by restating what we consider to be the main takeaways from the exercises presented here. The incentives to adopt automation technologies may be very

different across informal and formal employment and may imply that standard calculations in the literature, such as those presented in section 3, could significantly overestimate the threat of automation in emerging markets where the formal labor market commands a large share of total employment. Additionally, a robust feature of the data is that younger and less educated workers are the demographic groups whose employment is most at risk of being automated.

4.2 Wages, Cost Savings, and the Incentives to Automate

As previously discussed, the incentives to automate will depend, in part, on the wage savings that can be attained through automation since firms will seek to automate those jobs that result in the biggest net savings (net of the cost of adopting automation technologies). The process of automating employment will continue until firms reach the marginal worker for whom they are indifferent between keeping on the payroll or automating the job. In this section we explore the role that the economy's wage structure may play in shaping the incentives to automate.[29]

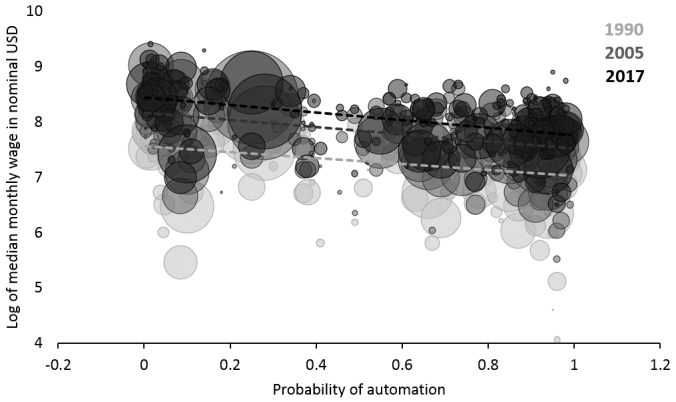
Figure 12 shows that median wages for an occupation are negatively related to the risk of automation in both Mexico and the United States. Since this relationship is consistent across several years, it can be argued that it precedes the penetration of automation technologies in the workplace. In addition, this negative relationship is robust to controlling for the median educational attainment in each occupation. This is suggestive of the possibility that occupations at high risk of automation may actually experience lower worker displacement than some less exposed occupations due to their comparatively lower wages, which dampen the incentives to automate.

Since automating employment is not costless, it might not be worthwhile to automate all jobs. Thus, considering the economic incentives for the adoption of automation technologies, we might be particularly concerned about the automation of jobs that not only have a high technological possibility for automation, but that, in addition, pay relatively high wages given that automating these jobs could imply important cost savings for firms. This kind of analysis would be ideally performed based on data disaggregated at the firm and occupational level, and controlling for productivity. Such data would allow for obtaining labor costs per efficiency unit with more detailed information on the cost structure faced by firms in the automation of

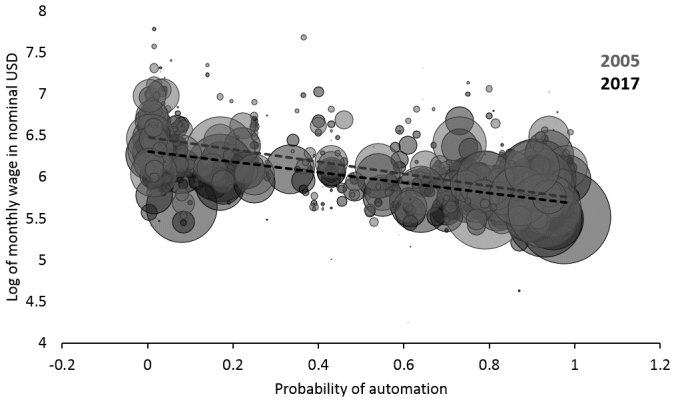
[29]Given that our exploration is illustrative in nature, the exercise adopts a partial equilibrium perspective. A richer appreciation of the role of wages in determining the extent to which automation technologies will be adopted in the economy would necessarily require a general equilibrium perspective to account for the endogenous adjustment in prices in response to changes in relative demands and relative supplies of different types of skills in the economy.

Figure 12: Wages and the risk of automation

(a) United States



(b) Mexico



Note: Authors' calculations based on data from ENOE, Current Population Survey, and Frey and Osborne (2017). Bubbles are proportional to an occupation's share in total employment.

different activities. Since this kind of detailed data is not available at the moment, we propose an illustrative exercise based on aggregate data.

Consider the subset of occupations that are at high risk of automation and, within this subset, rank occupations according to their contribution to the economy's wage bill.[30] We assume that high-risk occupations that command a large share of the economy's wage bill are at a relatively higher risk of being automated due to the potentially larger costs savings that they could imply.[31] For a lack of a more sophisticated terminology, we could define these

[30]The set of occupations that are at high risk of automation, according to Frey and Osborne's estimates, account for 48 percent of the formal sector wage bill in Mexico. The top 10 and top 15 occupations alone, according to their share in the wage bill, account for 22 and 26 percent of the formal sector wage bill, respectively.

[31]In the absence of information regarding the possibly heterogeneous costs of automating different task, the

occupations as occupation at *very high* risk of automation. For the purposes of our exercise we assume that the cost of replacing workers with automation technologies is only profitable for very high-risk occupations and we define as such the top 15 high-risk occupations (ranked by their share in the economy's wage bill).[32] The upper panel of Figure 13 presents the share in the economy's wage bill of occupations at high risk of automation, while the bottom panel reports our revised estimates for the share of employment at high risk of automation once we restrict our focus on the subset of occupations that have a high participation in the aggregate wage bill. By focusing on these occupation at very high risk of automation we discover some interesting patterns. In the short run,[33] 31.4 percent of the formal sector employment is at very high risk of being displaced due to the likelihood of adoption of automation technologies. This is a significant difference relative to the 57 percent that we estimated basing our analysis solely on the technical possibilities for automation. Furthermore, women are significantly more at risk of being displaced than men due to the likelihood of adoption of automation technologies.

Based on this exercise we would conclude that 14 percent of the total employment in Mexico is at very high risk of being displaced due to the ***likelihood of adoption*** (not merely the technological possibility of adoption) of automation technologies in the workplace. While our exercise is merely illustrative, it highlights that a risk assessment of the threat that automation poses for worker displacement could severely overstate the magnitude of the possible effects on labor markets if the assessment does not takes into account the incentives to automate that firms face.

4.3 Offshoring vs. Automation

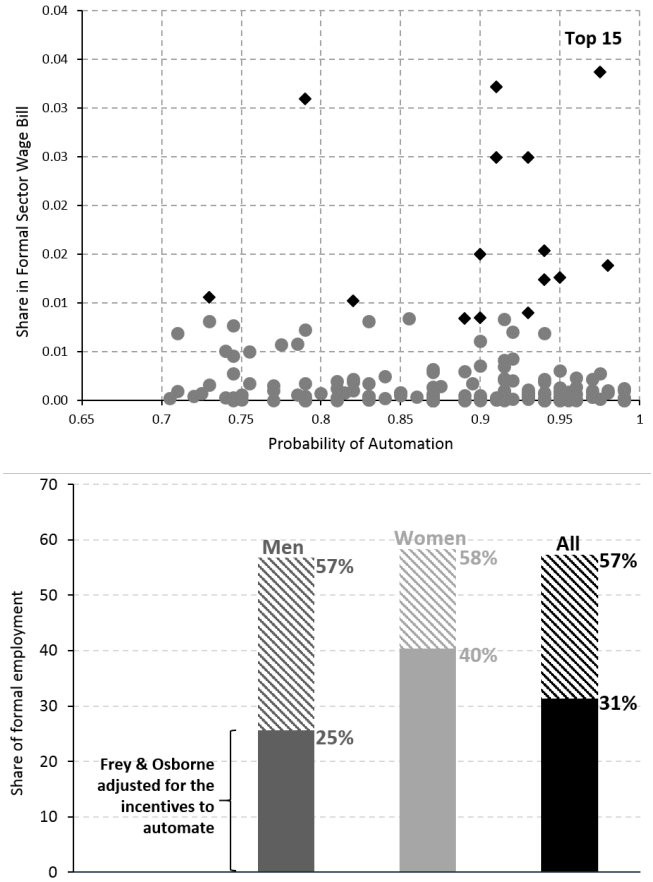
Following up on the discussion of the previous subsection, we emphasize that the probability estimates of Frey and Osborne may convey little information about which occupations will be most affected by the penetration of automating technologies in the workplace and the speed at which these technologies will be adopted, unless such estimates were systematically related to the cost of adopting automation technologies. Even in this instance, a risk assessment solely based on the Frey and Osborne probabilities would miss out on potential market adjustments

implicit assumption we make here is that these costs do not vary significantly across the occupations under consideration.

[32]These 15 occupations command 26 percent of the formal sector wage bill and their (unweighted) average probability of automation is 0.9.

[33]We say in the short run because our classification scheme is based on wages and the allocation of workers to occupations that are both endogenously determined in the economy.

Figure 13: Occupations at a very high risk of automation in Mexico



Note: Based on authors' calculations. The reported shares in the economy's wage bill correspond to the median share in the wage bill for the period 2013Q1-2017Q4.

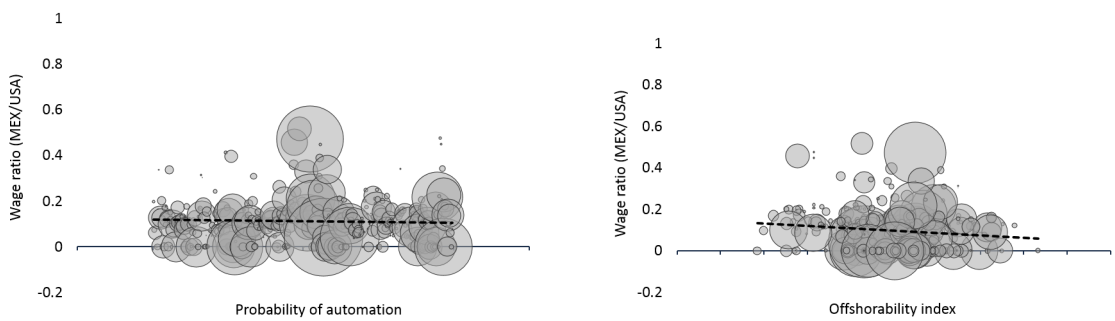
that may limit the extent to which automation actually takes place. For example, in an open economy such as the Mexican economy, the rapidly increasing ease with which production can be fragmented across national borders means that firms can re-organize production through both automation and offshoring.

In an open economy setting the threat of worker displacement can arise from both the prospect of automation in the workplace and the possibility to fragment production and offshore some or all of the tasks demanded by the firm. For example, the organization of production for firms located in the Unites States involves the choice between hiring domestic workers, automating local employment, or sending employment opportunities abroad (i.e. offshore). The profitability of each option will depend on comparative labor costs at home and abroad and on the cost of technology adoption relative to utilizing workers. Conversely,

in countries like Mexico where employment is offshored, offshoring could represent a force for job creation that may mitigate the impact of worker displacement due to automation.

Figure 14 presents relative labor costs between Mexico and the United States for 2017, calculated as the ratio of median wages across countries for each occupation. The left panel illustrates relative labor costs as a function of an occupation's probability of automation, while the right panel illustrates relative labor costs as a function of the ease with which an occupation can be offshored.[34] By looking at relative wages between Mexico and the United States it is not clear which US jobs are most likely to be automated or offshored, in this case to Mexico, given that relative wages appear to be unrelated to both the probability of automation and the offshorability of occupations.[35]

Figure 14: Comparative labor costs: Mexico vs United States



Note: Authors' calculations based on ENOE (2017), Current Population Survey (2017), Frey and Osborne (2017), and Autor and Dorn (2013). Bubbles are proportional to an occupation's share in employment in Mexico.

Under the optimal organization of production, firms will shed domestic workers in favor of either foreign workers (offshoring) or automation technologies. This means that the observed share of workers displaced because of automation can be overstated in an assessment that only

[34]The offshorability of an occupation is based on Autor and Dorn (2013) who classify occupations according to the extent to which an occupation involves routine vs. non-routine tasks. See also Blinder and Krueger (2013) for an alternative, but related, classification of the offshorability of occupations.

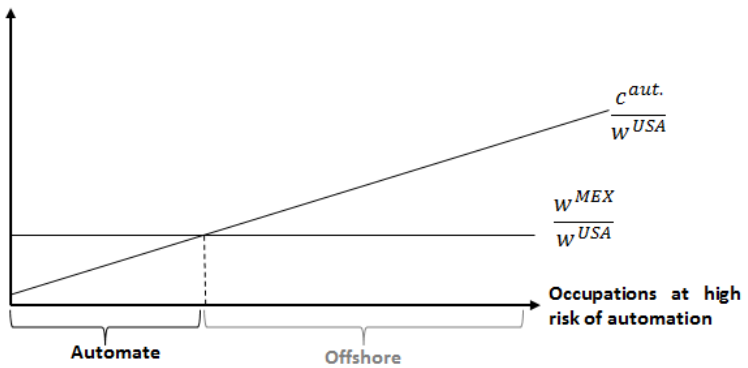
[35]We run a regression of relative wages by occupation, using the median wage for each occupation in the formal sector, on the probability of automation, the ease of offshorability of the occupation, and relative education levels in each occupation across Mexico and the United States. The estimated regression is:

$$\frac{w_j^{Mex}}{w_j^{US}} = -0.04 + 0.04q_j + 0.05q_j^2 - 0.01O_j - 0.005O_j^2 + 0.183^* \frac{educ_j^{Mex}}{educ_j^{US}}. \tag{4.1}$$

We find no statistically significant relation between relative wages and both the probability of automation (q) or the ease of offshoring (O). Relative education levels, however, are positively and significantly related to relative wages across Mexico and the United States.

considers the technical feasibility of automation and not the economic incentives that shape the decisions of firms regarding technological innovation/adoption and employment. If we focused on a narrow decision problem in which firms were deciding to either offshore a job to Mexico or automate a job at home, the flat profile of relative wages depicted in Figure 14 suggests that the cost of automation relative to labor costs in the United States would play a decisive role in determining which tasks/occupations to offshore and which to automate. This decision is illustrated graphically in Figure 15.

Figure 15: Offshoring vs. automation



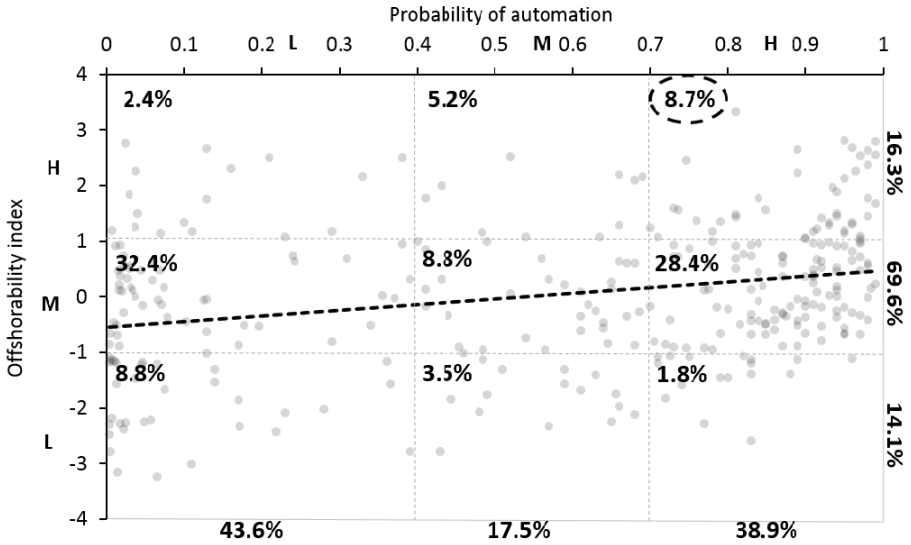
As a final exercise we revisit Frey and Osborne's estimate of the share of US employment at high risk of automation, but we cross their classification based on the probability of automation with the offshorability of occupations. Figure 16 presents the distribution of US employment across the probability of automation-ease of offshoring matrix, in which both offshorability and probability of automation have been divided into three groups: low, medium, and high. There is a positive, albeit imperfect, relationship between the possibility to automate an occupation and the possibility to offhshore that same occupation.[36] This means that the employment threat materializes through competition with foreign workers for some occupations, for others it results from competition against technology, while some occupations face the double threat of automation and offshorability.

Given the occupational distribution of employment in the United States for 2017, we estimate that 55 percent of workers are at high risk of being either automated or offshored, with 39 percent alone corresponding to those at high risk of being automated.[37] These numbers

[36]The Spearman rank correlation between the two indices is 0.31, statistically significant at the 0.1 percent level.

[37]The employment shares reported in Figure 16 are based on the share of employment that can be classified

Figure 16: Risk of automation vs. risk of offshorability in U.S. employment



Note: Authors' calculations based on Current Population Survey (2017), Frey and Osborne (2017), and Autor and Dorn (2013).

refer to the share of workers that are employed in occupations that can be potentially automated and/or offshored, not necessarily those that will actually be. They are consistent with research that has found that worker displacement in the United States has been primarily the result of technological progress rather than globalization. For occupations that are both at high risk of automation and high risk of being offshored, which we could refer to as occupations at high risk of displacement, it might be particularly difficult to disentangle whether worker displacement occurred as the result of automation or as the result of offshoring since these can be parallel processes in the re-organization of production. Due to Mexico's lower labor costs relative to the Unites States, a share of jobs at risk of being automated in the United States could actually be displaced due to offshoring rather than automation, especially if hiring labor in Mexico is relatively less expensive than automating employment in the United States. This implies that the estimated share of Mexican workers at high risk of automation, based solely on the estimated probabilities of Frey and Osborne, could be overstated by up to 9 percentage points.[38]

according to both the offshorability and automation indices. Thus, observations in which a worker's self-reported occupation is "other" or is not found in the list of occupations common to both indices are dropped from the sample. Given this double classification scheme, the total share of workers at high risk of automation reported here is 39 percent rather than the 44 percent we would obtain for 2017 if we were only classifying employment according to the probability of automation index.

[38]This figure would result from assuming that the occupations at high risk of displacement were offshored to Mexico.

5 Concluding Remarks

Given the increasing concern regarding the labor market disruptions that the adoption of automation technologies may cause, we provide a risk assessment for the Mexican economy regarding the share of workers at high risk of being displaced and the differential exposure to this risk across demographic groups. Using the estimates of Frey and Osborne (2017) for the automatability of occupations, together with the distribution of employment across occupations obtained from ENOE, we estimate that 65 percent of total employment is at high risk of being automated. Focusing only on formal sector employment, we find that 57 percent of employment is at high risk of being displaced by automation technologies. Across demographic groups we find that workers less than 25 years old and workers with less than a high school education are the groups most exposed to this threat. In particular, we find that human capital accumulation, through its effect on occupational choice, significantly reduces the probability that workers will be employed in occupations at high risk of automation. Thus, policies that incentivize human capital accumulation will be important in emerging markets, not only for the standard reasons (i.e. productivity growth and development), but also because they might facilitate the process through which automation technologies are incorporated into the economy's productive structure, while minimizing the adjustment cost in the labor market.[39]

Estimates that are solely based on the technical possibilities to automate, such as those presented in section 3 following Frey and Osborne (2017), might overestimate the magnitude of the share of employment at risk of being displaced because of automation by not incorporating into the analysis the economic incentives for the adoption of automation technologies into the workplace. We stress that the technological possibility for automating an occupation does not necessarily imply that it will be actually automated because it may not be profitable to do so. We argue that in emerging markets with a high degree of trade openness, such as Mexico, important factors affecting the pace at which these technologies are incorporated into the economy's productive structure are the size of the informal labor market, the wage structure across occupations, and the interplay between automation and other processes that induce re-organization in production, such as offshoring. For example, if to a first-approximation

[39] Trajtenberg (2018) lists the set of skills that will be required for employment in the era of AI and points out that it is now widely recognized that critical skills (hard and soft, cognitive and social) are acquired very early on in life and that failure to do so in early stages may be hard, or even impossible, to remedy later on. Thus, the prospective disruption that automation technologies may have on labor markets adds to the vast number of reasons why human capital policies that target early childhood development are paramount for economic growth and prosperity.

we assume that the adoption of automation technologies is not profitable or feasible in the informal sector, then we would estimate that 25 percent of total employment is at high risk of being automated, rather than 65 percent, given the prevalence of informality in the Mexican labor market. Similarly, focusing on occupations that are at high risk of automation while commanding a higher share of the economy's wage bill and assuming that those are the occupations whose automation would warrant the most significant cost savings, our estimate would be further revised to about 15 percent of total employment being at very high risk of automation. If we assume that, because of the relative labor cost structure between the two countries, occupations that are at high risk of automation in the United States could be offshored to Mexico, the share of Mexican employment at risk of displacement would further decrease.

Understanding how technological feasibility and economic incentives interact is an important direction for future work that is necessary to obtain more precise estimates of the number of workers that might be displaced by the adoption of automation technologies. It is also essential to design policies that can help current workers adjust to the risk of displacement and incentivize future workers to be prepared for the skills that the labor market of the future will demand. The need to retrain and transition workers to new occupations, perhaps even in new locations, might be highly disruptive and the policy debate on these issues would certainly benefit from better and more extensive data collection that can inform and guide solutions to the problem. Important efforts in this direction should include three essential elements. First, more detailed and accurate data regarding both the offshoring of employment and the adoption of automation technologies across time and industries. Second, a more nuanced and sophisticated separation of occupations/tasks (e.g. Ph.D. economist vs. bachelor degree economist, which might be both classified as 'economist' even if the nature of tasks they perform may be substantially different). Third, data that can be informative regarding the cost structure that firms face for the automation of different tasks and/or occupations. A more comprehensive perspective regarding the ways in which automation technologies will affect aggregate productivity and employment will serve to better design policies that, rather than slowing down the pace of technical change to protect potential losers, ensure that more people are able to share in the aggregate benefits that technological change can provide.

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