Is the pandemic fast-tracking automation in developing countries? Preliminary evidence from Colombia[1]

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Abstract

We assess whether the pandemic had a larger impact on labor in occupations more prone to automation. We analyze the change in job openings and employment during the pandemic using data from the Colombian Public Employment Services (SPE) and household Surveys. We estimate event-study models to evaluate the differential effect of the pandemic on job openings and salaried employment by the potential degree of automation of each occupation. The results indicate that both vacancies and salaried employment fell more in highly automatable occupations, and their recovery has been considerably slower. The differential effects on employment are mostly driven by occupations that were more affected by the mobility restrictions, as well as female and workers over 40.

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[2] The opinions expressed here are not necessarily those of either the Banco de la República or its Board of Directors. The authors are fully responsible for any remaining errors. The authors are researchers of Subgerencia de Política Monetaria e Información Económica of the Central Bank of Colombia. ♣Corresponding author, lflorefl@banrep.gov.co.

1. Introduction

Automation has accelerated over the last decades, mainly driven by the growing use of robotics and information technologies (Acemoglu and Autor, 2011; Autor et al, 2003; Autor and Dorn, 2013). Short run evidence suggests that this process reduces employment, particularly in more routine and less qualified occupations. However, the evolution of technological progress suggests that even the less routine jobs can be automated (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017). The evidence of the effects of the automation process in longer horizons is still unclear. Autor (2013) and Frey and Osborne (2017) suggest that automation increases structural unemployment because, in the long run, the related job destruction is larger than the corresponding creation. In contrast, other authors suggest that the automation process replaces but also complements jobs, so in the long run there is an equilibrium between automation and employment (Acemoglu and Restrepo, 2018a,b; Autor, 2015)[3]. In any of these cases, the automation process replaces less qualified jobs and creates more qualified jobs (Autor, et al, 2003). A process like this would increase the relative wages of qualified jobs (Acemoglu and Restrepo, 2018c; Autor, 2015), with an increase on wage inequality (Prettner and Bloom, 2020; Prettner and Strulik, 2020).

Recent evidence suggests that the Covid-19 pandemic may have accelerated the automation process. For example, for the United States, Ling and Sáenz (2020) found that those occupations with a greater probability of being automated experienced a larger drop in employment with the arrival of the Covid-19. At the same time, many of these automated jobs did not recover at the same pace as other segments during the recovery phase. This translates into a permanent loss of jobs, especially those most vulnerable to confinement and social distancing measures. Further, although the economic recovery has allowed some people to return to their traditional jobs, the demand for new jobs (measured with online vacancies) has been relatively moderate, especially for people with lower-skill occupations

[3] The main difference between these two analyses is given by the different estimation of automation across occupations versus across tasks. When we study the automation process across occupations, there is an overestimation, since occupations are more aggregated than task. For example, the accountant occupation has several tasks such as reviewing invoices, taking stock of the company and writing reports among many others; not all of these tasks can be automated; then, it could be said that the estimation of automation by tasks is more disaggregated and it will depend on each particular firm. In a particular occupation there may be some tasks that are not automatable, therefore they need to be performed (Arntz et al, 2017).

(Chem, 2020). Similar results were found by Costa Dias et al (2020) and Dolado et al (2020) in the case of the United Kingdom and Spain[4]. Likewise, Saadi and Yoo (2021) show that lower-skilled workers are at a higher risk of being displaced by a robot than higher-skilled workers. These authors also showed that the adoption of robots increased during the pandemic, especially in the public health sector. One of the few studies assessing the effect of the pandemic on automation in developing countries is Egaña del Sol et al (2021). The authors show that in Chile, job recovery has been considerably slower in sectors with a greater availability of technologies that facilitate automation.

We study the potential effect of the Covid-19 pandemic on the automation process in Colombia, a country that exhibits a labor market characterized by a combination of low productivity with particularly high informality and unemployment rates. We assess whether the pandemic had a differential impact on the demand of occupations that are more prone to automation. The demand for new jobs during the pandemic is measured using vacancies by occupations collected by the Colombian Public Employment Services Bureau (SPE). The probability of automation of each occupation is measured using the Frey and Osborne (2017) and Nedelkoska and Quintini (2018) methodology adapted to the Colombian case. Finally, we use an event-study approach to evaluate the differential effect of the pandemic on the job openings from the SPE and on the total salaried employment based on household surveys, according to the occupations' potential degree of automation.

The results indicate that during the pandemic, there were significant lower job openings for occupations with greater potential of automation compared to those less automatable. These effects are sizable and persisted until our last observation (March 2021). However, when using employment stocks measures such as salaried workers and salaried formal workers, we find significant differential effects only between February 2020 and August 2020. Moreover, we find that the automation process has been differential by age and gender. For the case of salaried workers, we found that the negative effects on employment are mostly driven by the impact on workers over 40 years old, for whom the gap between more and less automatable occupations is the largest and more persistent since March 2020, For workers under 25 years old, we find that the difference is small during the first months

[4] These authors found that during the pandemic, job losses have been concentrated in segments of the labor market with low-skilled occupations as is the case of labor-intensive occupations associated with personal services with some physical proximity such as hotels, restaurants, recreational activities, among others.

of the pandemic and become positive and significant since November 2020. This finding implies a re-composition in highly automatable occupations in favor of younger workers. This is particularly the case of those older workers with low skills than are concentrated in in highly automatable occupations. In terms of gender, we find that automation is affecting more severely and persistently the labor market of female workers. The estimated effect is almost twice as large for females compared to males during the last months of the sample.

We contribute to the empirical literature of automation in at least two ways. First, we estimate the automation process in a middle-income country with low productivity, and high level of informality and unemployment. The evidence of automation in developed economies suggests a long-term equilibrium between automation and employment (Acemoglu and Restrepo, 2018 a,b; Autor, 2015); nevertheless, it is not clear that this is also the case for developing countries with high informality and unemployment. In the latter case, the automation process can have a negative and long-term effect on unemployment, if this process is not complemented with investments in human capital. Despite the above, there is a big potential for automation in developing economies, with important benefits in productivity and wages. Second, we contribute to the literature in the adaptation of Frey and Osborne (2017) and Nedelkoska and Quintini (2018) methodology for the case of developing countries, where such information is scarce.

The remaining of the paper is organized as follows. Sections 2 and 3 present the conceptual framework and the Colombian labor market during the covid-19 pandemic, respectively. Section 4 describes the data and the empirical strategy. Section 5 presents the results, and the last section concludes.

2. Conceptual framework

We base our short-term analysis of the differential effects of the pandemic on jobs on a static version of the task-based model of automation from Acemoglu and Restrepo (2018a) [5], where innovation replaces tasks previously performed by labor with robots (automation) and

[5] This framework is related to the model in Acemoglu and Restrepo (2018b,c), and builds on Zeira (1998), Acemoglu and Zilibotti (2001) and Acemoglu and Autor (2011).

creates new tasks for which labor has a comparative advantage. The simple version of the model assumes that capital is fixed and exogenous[6].

Each task is produced by combining labor or capital with a specific task intermediate. There is a technological constraint on automation, such that task $i \leq I$ are technologically automated (i.e. these are feasible to be produced with capital); however, their production with capital or not depends on relative factor prices. Moreover, task $i > I$ are not technologically automated, and they should be produced with labor. Given that tasks are produced competitively, the price of producing any task, $p(i)$, will be equal to the minimum unit cost of production:

$$p(i) = \begin{cases} min\left\{R, \frac{W}{\gamma(i)}\right\}^{1-\eta} & if\ i \leq I \\ \left(\frac{W}{\gamma(i)}\right)^{1-\eta} & if\ i > I \end{cases} \tag{1}$$

Where W denotes the wage rate and R denotes the rental rate of capital. Therefore, the unit cost of producing tasks $i > I$ is given by the effective cost of labor, $\frac{W}{\gamma(i)}$; and the unit cost of producing tasks $i \leq I$ is given by $min\left\{R, \frac{W}{\gamma(i)}\right\}$. This last term, reflects the fact that capital and labor are perfect substitutes in the production of automated tasks. Therefore, firms will choose to produce the task with labor or capital depending on which factor has the lower effective cost: R or $\frac{W}{\gamma(i)}$.

The covid-19 pandemic directly affects the optimal allocation of tasks through a sudden increase in labor cost relative to capital. On the one hand, governments have put in place strict mobility restrictions, which considerably reduced labor supply in most industries. On the other hand, the fear of contagion may also raise the opportunity cost of workers, further increasing the price of labor[7]. Moreover, given the uncertainty regarding the length

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[6] The model assumes that the economy produces a unique final good Y by combining a unit measure of task, $y(i)$, with an elasticity of substitution $\sigma \epsilon (0, \infty)$: $Y = \tilde{B}\left(\int_{N-1}^{N} y(i)^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}}$, where $\tilde{B} > 0$ and all tasks and the final good are produced competitively. It is assumed that the limits of integration run between $N-1$ and N to guarantee that the measure of task used in production always remains at 1. A new (more complex) task replaces or upgrades the lowest-index task. Thus, an increase in N represents the upgrading of the quality (productivity) of the unit measure of task.

[7] The hospitality and tourism sector; and health sector are a good example on how robots have played an important part during the pandemic (see Fusté-Forné and Ivanov, 2021; Seyitoğlu, and Ivanov, 2021; Beane, and Brynjolfsson, 2020; Bogue, 2020; Aymerich-Franch and Ferrer, 2020; Di Lallo et al, 2021; Seidita et al, 2021; Magid et al, 2021; Gupta et al, 2021). Moreover, according to Bloom and Prettner (2020), automation,

of the pandemic and the vaccination campaign, this increase in labor cost can be perceived as long-lasting. Overall, the growing labor cost during the pandemic is expected to accelerate automation (Bloom and Prettner, 2020).

Automation also has international spillovers. Kugler et al (2020) find that automation in the US replaced Colombian production with imports, displacing workers in the sectors with greater potential of automation (Kugler, et al, 2020). This implies that the observed losses in labor demand could be driven by foreign rather than local automation. In the last section of the paper, we address this point using detailed import data by sector. Specifically, we assess the impact of Covid on the import of capital goods, reflecting local automation, and on import substitution, reflecting foreign automation.

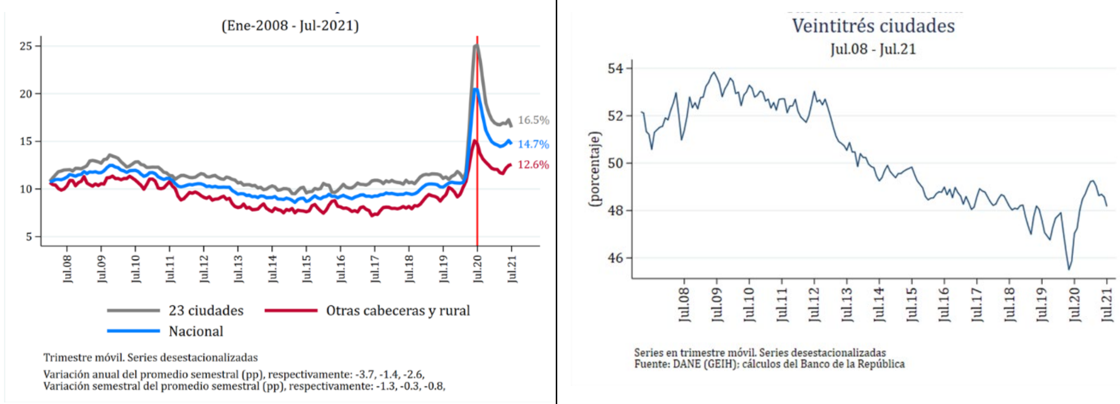
3. Labor market and covid-19 in Colombia

As in many other countries, the Covid-19 pandemic triggered a massive economic turmoil in Colombia, with a severe disruption of its labor market. Despite the efforts of local authorities to counter the downturn with fiscal and monetary policy measures, GDP shrank by 6.8 percent in 2020, the economy's largest decline in its modern history. The contraction in employment was even larger, 11 percent in 2020, and is not expected to recover as quickly as in developed countries. **Figure 1** presents the recent evolution of the unemployment rate (panel A) and the informality rate (panel B). As of July 2021, the national unemployment rate was still around 4pp higher compared to the period before the pandemic, with a worse picture for the urban unemployment rate. A similar behavior shows the informality rate, which presented an important increase during the worse period of the pandemic (close to the 50%), and, up to July 2021, has not come back to his previous levels.

robotics, modern information and communication technologies, and artificial intelligence have been incredibly useful in fighting the pandemic, as well as in alleviating its economic consequences.

Figure 1

Panel A: Unemployment rate	**Panel B:** Informality rate



Source: GEIH-DANE, authors calculations.

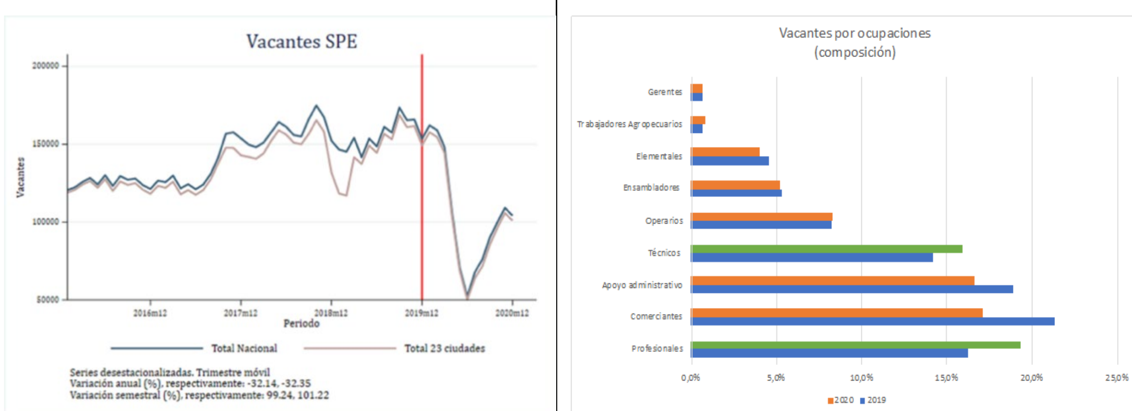
The impact of Covid-19 on employment was the result of a mixture of different forces that interacted simultaneously once the pandemic hit in March 2020. The main causes included: (i) the individuals' responses to the presence and propagation of the disease (e.g. behavioral changes that shifted the demand of goods and services due to fear of contagion, work absenteeism as a result of the illness, etc.); (ii) the impacts from the sudden and simultaneous macroeconomic shocks that hurt the whole economy (e.g. disruption of supply chains, reduction in income from international trade and remittances, increase in volatility of asset prices and risk premia, etc.); (iii) the set of mobility restrictions that authorities implemented to promote social distancing to curb contagion (Morales et al. (2021), present a decomposition of the contribution of each of the latter sets of causes in the Colombian labor market outcomes in 2020).

Job losses were unequally distributed across different groups of workers. First, women were more affected relative to men: female employment fell 15 percent on average in 2020, versus eight percent of male employment (Cuesta and Pico, 2020; Garcia-Rojas et al, 2020; Bonilla et al, 2021a). Second, the impact was more severe for young workers: employment of individuals 25 years old or younger fell 16 percent, versus 10 percent of individuals in other ages (Bonilla et al, 2021b). Third, due to the nature of the crisis, job losses were largely heterogenous across sectors, and even within sectors, job destruction was disproportionally larger for smaller and less productive firms (Morales et al, 2021; Bonilla et al, 2020).

Regarding job offers, we present the evolution of total online job openings during the pandemic in **Figure 2**. Job openings declined 70 percent in April 2020 relative to January 2020. Since May, vacancies started to recovery but their levels at the end of 2020 were still far from those observed before the pandemic (Panel A of Figure 2). When we disaggregate by occupations, we see that in general most of the vacancies come from retail activities, administrative support and professional occupations. However, there were important changes in the composition of occupations between 2019 and 2020. Particularly, the share of vacancies for both professional and technical jobs had important gains in 2020, whereas those from retail, administrative support, and elementary occupations experienced considerable losses (Panel B of Figure 2). These compositional changes are signs of a shift in the relative demand for labor, for which we find evidence that can be linked to different occupation´s attributes (see next section).

Figure 2

Panel A: Job opening	**Panel B:** Job openings by occupations



Source: SPE, authors calculations.

4. Data and empirical strategy

4.1 Data

We characterize the evolution of the Colombian labor market using two main sources of information: (i) online job vacancies posted by SPE, and (ii) household surveys (GEIH) from the National Department of Statistics (DANE). The SPE is an administrative unit created in 2013 by the Colombian Ministry of Labor, with the aim of enhancing labor intermediation policies. According to Law 1636 of 2013, all public and private employers in Colombia are required to report their vacancies to the SPE, either through private providers (authorized recruitment agencies, online job portals, etc.) or through the public employment agency (Amaral et al, 2021). Naturally, most of the employers who fulfill this law requirement offer jobs that are covered by the social security system, so it can be assumed that the job posts correspond mainly to the salaried and formal segments of the labor market.[8] The job openings can be posted with the intention of either replacing a worker separated from the firm or filling new jobs created by firms; however, we cannot distinguish between these two possibilities so we use both types of offers interchangeably, and we will refer to them simply as vacancies. The occupations we consider are the following: 1. Managers, 2.Professionals, 3. Technicians and Associate Professionals, 4.Clerical support workers, 5. Service and sales workers 6. Skilled Agricultural, Forestry and Fishery Workers, 7. Craft and Related Trade Workers, 8.Plant and Machine Operators and Assemblers, 9. Workman in elementary occupations.

The GEIH is the monthly household survey collected by the DANE used to compute the official labor market statistics in Colombia. The survey is representative for the main urban labor markets in Colombia, and includes an occupation question that is coded in the CNO-70 system. We create a crosswalk between this classification and the 1-digit ISCO 08 adapted for Colombia used by SPE. We then aggregate monthly employment by occupation and city, which will be our unit of observation. We focus on salaried workers, and formal salaried workers[9].

Panel A of Table A1 in the Appendix displays summary statistics of the total number of annual job posting offers collected by the SPE in the period 2015 to 2020, indicating that, in the average year, around 1.2 millions of vacancies are posted in the main 23 cities of the

[8] In Colombia, as in many other developing countries, the labor market is specially segmented with an important prevalence of informality (jobs that do not comply labor regulations and thus are not covered by the social security system). However, most of this employment correspond to self-employment jobs or jobs in small business where the possibility of automation is low.
[9] Formal workers report contributing to the Colombian social security system.

country. In order to assess how representative this data is, we compute the annual amount of hires in the formal and salaried segments of the same cities implicit in the records of the GEIH[10]. We find that in this segment the survey estimates that there are approximately 6.6 millions of hires in the average year. So, if all vacancies were filled, the mechanism of job postings in the SPE would be facilitating on average around 20 percent of the whole hires in the urban salaried labor market, a proportion that is increasing over time[11].

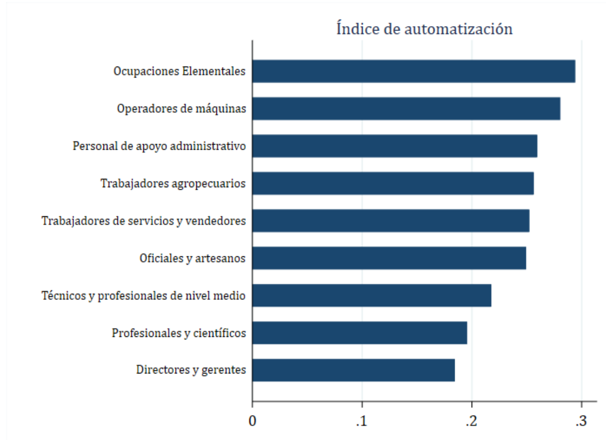
We measure the probability of automation of each occupation in Colombia following Nedelkoska and Quintini (2018), who in turn build on Frey and Osborne (2017). We estimate the probability that a specific profession can be automated based on data from the Programme for the International Assessment of Adult Competencies (PIACC), which is available for all countries in the OECD[12]. We adapt the probability of automation to the Colombian standards by weighting the participation of each OECD country in the Colombian imports, as a way to account by the adaptation process of technology in Colombia. This results in a standardized index for automation at 2-digit ISCO08 level. Next, we average the index for each city and each occupation at the 1-digit ISCO08 level, using the GEIH expansion factors as a means to account for the composition of the Colombian labor market. **Figure 3** presents the probability of automation for each occupation in our sample. As expected, occupations with a higher probability of being automatable are those with low level of competence, such as elementary occupations and machine operators.

[10] Due to a change in the implementation of the survey in the first months of the pandemic, (DANE introduced telephone interviews instead of in-person), the household survey trimmed many questions of the original roster, and particularly those that allow us to compute hires. This explains why hires are not available for the total 2020.

[11] By replicating the exercise in the pooled data but exploring now differences in major occupation codes (1-digit ISCO 08 adapted for Colombia), in Panel B of Table A1 we show that the above ratio can be as high as 55 percent for some occupations, especially for those related to professional activities.

[12] By the time of the indexes of automation were constructed Colombia was not part of the OECD. To enhance the precision of these measures, we compute an average of the index for each profession weighting for the share of each country exports to Colombia during the period 2000-2007.

Figure 3: Measures of automation by occupation



Source: Authors calculations.

4.2 Empirical strategy

We assess whether the pandemic had a differential impact on occupations that are more or less prone to automation using an Event Study (ES) design. We regress job-posting vacancies collected by the SPE as a function of the automation variable (also we include the level of salaried employment as dependent variable). We interact this variable with month dummy variables for the post-pandemic period: January of 2020 to March 2021. The estimated equation can be represented as:

$$ln(V_{jct}) = \sum_{\tau=1}^{T} \beta_\tau \, auto_{cj} \times D_\tau + \gamma\theta_{ct} + \delta_{jc} + \delta_t + \varepsilon_{jct} \qquad (2)$$

The reference period is December 2019, the period before the World Health Organization (WHO) declared the covid-19 outbreak as a public health emergency of international concern. The dependent variable is the natural log of job posting offers in the profession *j*, in a city *c*, at the time *t*. We control for individual effects for each combination of city-profession and by month fixed effects. The model also controls for the disease propagation at each city θ_{ct} (measured as the number of death per million people of working age.). This design allows us to test whether before the declaration of the pandemic, there were systematic differences at the automation margin. In addition, the design allows us to assess whether after the pandemic, arguably as a result of it, these differences increase in magnitude and significance.

The coefficients that multiply the automation variable for the months before and after the pandemic show if the deterioration of the job posting vacancies is different given the level of automation of each profession. A potential identification problem may arise if the labor demand for salaried employment is affected by the general effect of the disease. To overcome this difficulty we control for city fixed effects. Further, as we show in the next section, we find no evidence of pre-trends, which indicates that occupations (salaried employment) with more or less probability of automation exhibited similar trends in job vacancies before the pandemic.

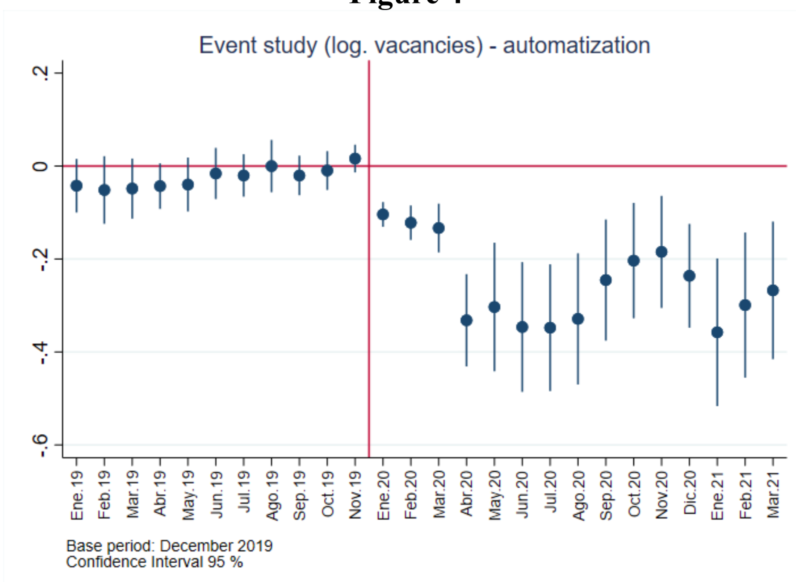
5. Results

We assess the differential effects of the pandemic on occupations that are more or less prone to automation. We base our analysis on two independent measures of employment: job posting offers from the SPE, and total salaried employment based on the household survey (GEIH). We then estimate the heterogeneous effects by age and gender; and finally, we assess whether automation has been more pronounced in occupations and sectors that were more affected by the mobility restrictions enacted at the beginning of the pandemic.

5.1. Automation, job posting, and employment

We begin our analysis by estimating the differential effects of the pandemic by the likelihood of automation on new job vacancies in **Figure 4**. This measure reflects the demand for new formal jobs in the economy, and is related with the more formal segment of the economy. The first result to highlight is that we find no evidence of pre-trends, which indicates that occupations with more or less probability of automation exhibit similar trends in job vacancies before the pandemic began. As early as January 2020, we find that automatable occupations were losing vacancies more rapidly than the rest, suggesting a quick adjustment process of the country's labor market. Between January and March, the estimated differential effect is near -1.3pp (percentage points), which implies that occupations that are more likely to be automatable (present an automation index one standard deviation above the average), have presented an additional reduction on the job posting vacancies after the pandemic. The gap between occupations that are more and less susceptible to automation widens considerably in April, when the sanitary emergency is declared and the national lockdown is enacted. The estimated differential effects oscillate around -0.35pp until August, when the lockdown measures begin to relax. After this, the gap closes for some months, with a minimum difference of -0.2pp in November. In December, the country is hit by a second wave of contagions, and the differences started to grow again, reaching a new maximum close to -0.4pp in January 2021 (Figure 4).

Figure 4

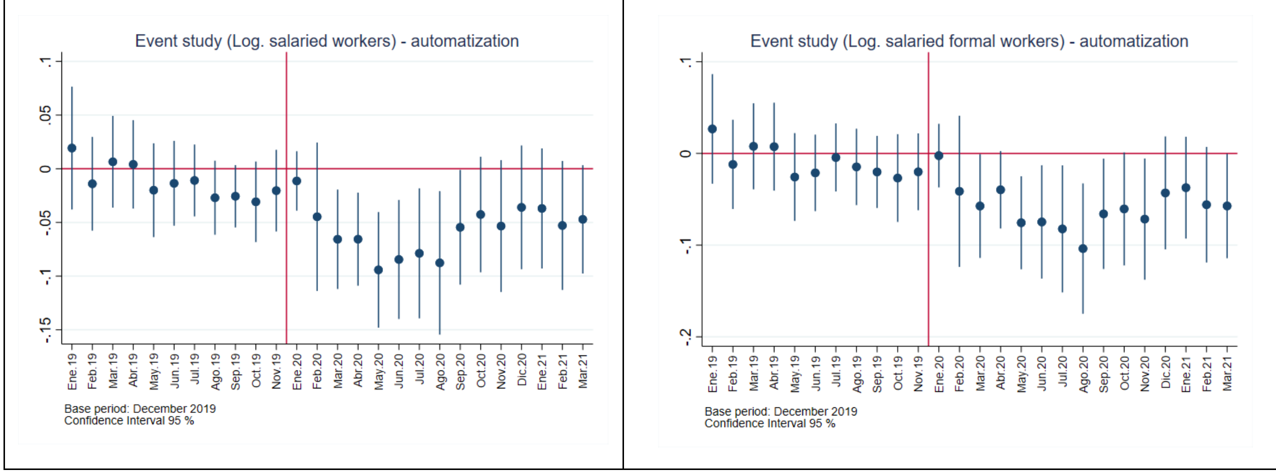


Source: SPE, GEIH-DANE, authors calculations.

Results are fairly similar when we use employment measures based on household surveys. **Figure 5** shows the differential effect of the pandemic on total salaried workers (Panel A), and total formal salaried workers (Panel B). In both cases, we find no significant differences in the pre-treatment period, and negative effects starting February 2020. Interestingly, total employment reflects less anticipation than job vacancies, as estimates are only statistically significant since March. The largest effects are found between May and August, with estimated effects near 10%. Since then, the gap has stabilized around 5%, with less precise estimates. This may reflect that total employment measures account for the stock of jobs, while job posting vacancies capture the future trend in the job flows, moreover, as we before the job posting vacancies are more representative in those salaried high-skill occupations, which can explain part of this differential, (see Panel B of Table A1 in Appendix). In general, our results are in line with Ling and Sáenz (2020), (for the case of United States) and Cruz et al. (2020) (for the case of Chile), who found that the occupations which present a higher likelihood of automation are also those who present a higher fall during the pandemic period.

Figure 5

Panel A. Salaried workers | **Panel B. Salaried formal workers**



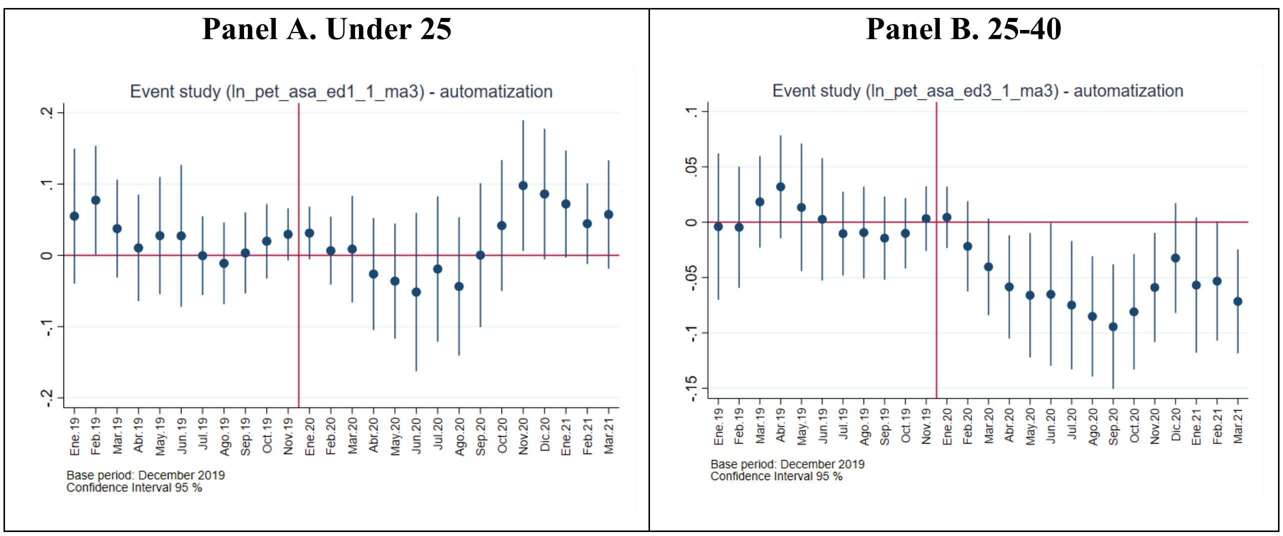
Source: SPE, GEIH-DANE, authors calculations.

Overall, our findings indicate that highly automatable occupations not only lost more jobs during the first months of the pandemic but are also recovering at a considerably slower pace. The persistence of the job-recovery gap between occupations suggests that the pandemic could have large term effects on the labor market, permanently reducing the demand for highly automatable occupations. The potential acceleration of the automation process in Colombia, calls for reallocation of human capital towards occupations with higher skills, a process that requires permanent and pertinent investments in human capital.

5.2. Heterogeneous effects by age and gender

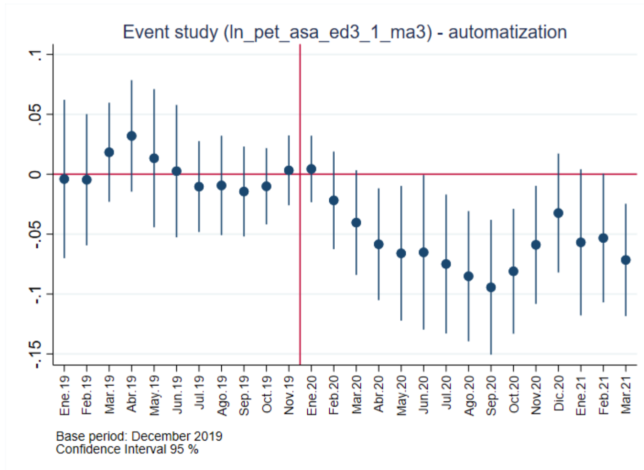
Recent literature has presented heterogeneous effects of the automation process by different levels of skills, being the low skill-occupations at higher risk of being automatable (Chem, 2020; Costa-Dias et al, 2020; and Dolado et al, 2020). Moreover, workers such as women and older workers with low-skills are the most affected during the pandemic (Garcia-Rojas et al, 2020; and Bonilla et al, 2021a). Therefore, in our context, we explore whether during the pandemic, the automation process has been differential by estimating separate regressions by age, and gender[13] for salaried workers in Figures 6 and 7, respectively. We also replicate these estimations for salaried-formal jobs, finding similar results (see Appendix B, Figures B1 and B2). The negative effects on employment are mostly driven by the negative effects on workers over 40, for whom the gap between more and less automatable occupations has been large and persistent since March 2020. For this age group, the largest estimated effect is reached in September 2020. Adults between 25 and 40 experience a considerably smaller effect, in magnitude and significance that converges to zero since January 2021. For workers under 25, we find that the difference is small during the first months of the pandemic, and become positive and significant since November 2020. This implies that, in addition to the job losses, there is a re-composition in highly automatable occupations in favor of younger workers.

Figure 6



[13] Due to a change in the implementation of the survey in the first months of the pandemic some variables such as education level and size of firm where the worker belongs were not collected, therefore we cannot explore the heterogeneous effects of automation through these characteristics.

Panel C. Over 40



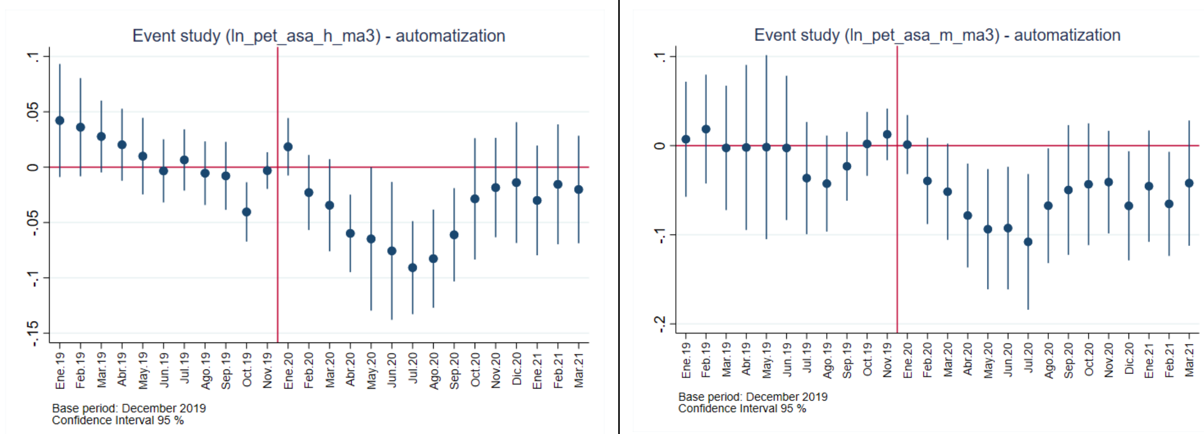
Source: SPE, GEIH-DANE, authors calculations.

The difference between genders is more subtle. While the estimated coefficients follow a similar pattern, the magnitude of the effects is consistently larger for females. This is reflected in a sharper decrease during the first months of the pandemic, and a more persistent gap afterwards. The estimated effect is almost twice as large for females than males during the last months of the sample. Therefore, automation is affecting more severely and persistently the labor market of female workers (Figure 7). This effect can be the result of two thigs: first women are more concentrated in highly automatable occupations and second, after losing the job because the pandemic they are also less likely to participate in the labor market (Garcia-Rojas et al, 2020).

Finally, there heterogeneous results support those found by Kugler et al (2020), who study how the automatization process in the US produce job displacement in Colombia from 2011 to 2016. The authors found a negative displacement effect for women, older workers and workers employed in small and medium sized enterprises in Colombia for the period 2011 to 2016.

Figure 7

Panel A. Male | **Panel B. Female**



Source: SPE, GEIH-DANE, authors calculations.

5.3. Heterogeneous effects by mobility restrictions

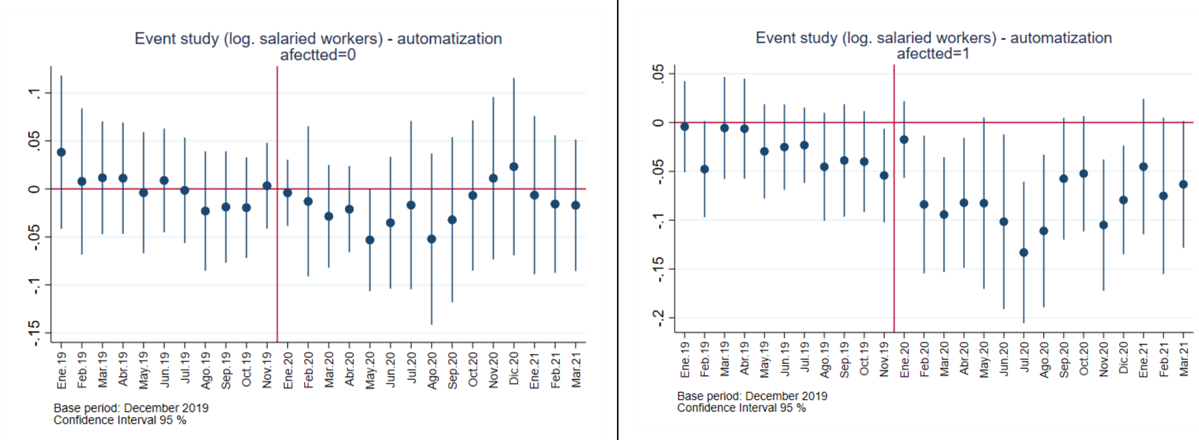
Finally, we explore the heterogeneous effects of the pandemic on automation by the incidence of the mobility restrictions enacted at the beginning of the pandemic[14]. To assess this, we estimate separate regressions by occupations that were excluded and non-excluded from the mobility restrictions. During March and April 2020, the Colombian government implemented strict mobility restrictions for all individuals except those working in a small set of sectors classified as essential. These essential sectors included public administration, finance, agriculture, and public utilities and the sectors that were part of their supply chains. (Morales, et al, 2021). We use these mobility restrictions and classified the occupations that belong to the excluded and non-excluded sectors to evaluate a differential effect of the automatization process. Panel A from **Figure 8** shows the results of those occupations without mobility restrictions. In this case, we found that in the sectors without restrictions, there was not a differential effect on occupations by the likelihood of automation. However, for the case of occupations located in a sector with mobility restrictions, the differential effect by the likelihood of automation is negative and significant. Moreover, these results are

[14] For a more comprehensive evaluation of the effect of the mobility restrictions on the employment in Colombia see Morales, et al, 2021.

significant even a long period after the mobility restrictions were eliminated (Panel B, Figure 8). These results are not surprising; as we mentioned before, the mobility restrictions could affect the optimal allocation of tasks through a sudden increase in the cost of labor relative to capital, accelerating the process of automation, especially among these non-excluded sectors. These sectors may see the automation as an alternative for compensating the cost of future mobility restrictions and also as a mechanism to control the disease himself.

Figure 8

Panel A. Excluded | **Panel B. Non-excluded**



Source: SPE, GEIH-DANE, authors calculations.

6. Exploring the channel of automation

In this section we explore the possible mechanisms in which such automation is taking place. In the first place, we are exploring how imports of machinery and equipment behave during the same period using also event-study methods. A second channel is through the acceleration of the automation process of a key trading partner such as US, that can also affect the automation process in Colombia (Kugler et al, 2020). In this case, we explore if the level of exports haw fall in sectors which are more or less prone to automation. (In process).

7. Conclusions

We estimate event study models to evaluate the differential effect of the pandemic on job openings and total salaried employment according to the degree of automation. We find that during the pandemic, there has been a significantly lower job opening for occupations with greater potential of automation than those that are less automatable. These differences are significant and persisted until our last observation, being around -0.3pp in March 2021. Moreover, when using salaried employment, we find a significant negative difference that starts from February 2020 and ends in August 2020 (nearly 10% difference). However, since then, the gap has stabilized with less precise estimates.

Moreover, we also explore whether our results are heterogenous by demographic characteristics such as age and gender. We found that the negative effects on employment are mostly driven by the negative effects on workers over 40, for whom the gap between more and less automatable occupations has been large and persistent since March 2020. Adults between 25 and 40 experience a considerably smaller effect, with magnitudes that converge to zero since January 2021. For workers under 25, we find that the difference is small during the first months of the pandemic, and become positive and significant since November 2020. This implies that, in addition to the job losses, there is a re-composition in highly automatable occupations in favor of younger workers. In terms of gender, we find that the magnitude of the effects is consistently larger for females. This is reflected in a sharper decrease during the first months of the pandemic, and a more persistent gap afterwards. The estimated effect is almost twice as large for females than males during the last months of the sample.

Furthermore, we explore whether the automation process has been differential by occupations that presented mobility restrictions. We found that there is a significant differential effect by the likelihood of automation, mainly in sectors with mobility restrictions. These results suggest that the mobility restrictions, imposed at the beginning of the pandemic, increased the cost of labor relative to capital, and that automation could have been an alternative to compensate the cost of future mobility restrictions, and also a mechanism to control the disease himself.

So far our preliminary results show a lower recovering on the job-posting, suggesting that the pandemic could have large term effects on the labor market, reducing permanently the demand for highly automatable occupations. This potential change on the labor demand might imply a reallocation process of the human capital that require of a permanent and pertinent training. In a country with high level of informality and unemployment such as Colombia, this could produce a structural mismatch between the skills required by the demand and the skills offered in the labor market (Petrongolo and Pissarides, 2021), inducing a negative effect on the long term unemployment rate (Bonilla et al, 2021b).

Given the latter empirical evidence, it is likely that the Covid-19 pandemic could have affected the optimal allocation of tasks among different occupations, accelerating the automation process in Colombia. In a work in progress (Section 6), we are exploring the possible mechanisms in which such automation is taking place. A first possible channel is a simple substitution of labor for machinery from firms that remain in the market. We are exploring how imports of machinery and equipment behave during the same period using also event-study methods. A second channel is through the acceleration of the automation process of a key trading partner such as the US, affecting indirectly the automation process in Colombia (Kugler et al, 2020). The pandemic could also have generated this type of spillover effect on automation in Colombia.

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Appendix

Appendix A Table A1: Summary statistics of vacancies from SPE

Panel A. Annual vacancies 2015-2020

Year	Total vacancies (SPE)	Hirings (GEIH-DANE)	Vacancies / Hirings
2015	748644	7068081	0.106
2016	1369279	6924380	0.198
2017	1334234	6521437	0.205
2018	1523996	6256743	0.244
2019	1482686	6404943	0.231
2020	1004085	NA	NA
Total 2015 -2019	6458839	33175584	0.195
Total 2015 -2020	7462924	NA	NA
Annual average	1243821	6635117	0.197

Panel B. Total vacancies 2015-2019

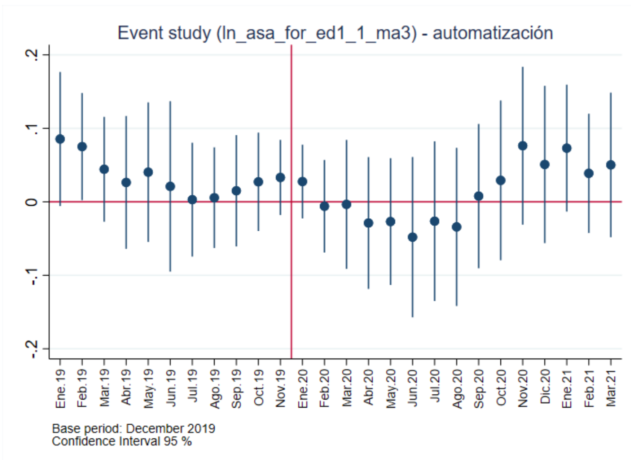
Major occupation	Total vacancies (SPE)	Hirings (GEIH-DANE)	Vacancies / Hirings
Managers	63562	841714	0.076
Professionals	1209152	2381206	0.508
Technicians and Associate Professionals	976386	1783482	0.547
Clerical Support Workers	1360939	4109964	0.331
Services and Sales Workers	1654398	11380537	0.145
Skilled Agricultural, Forestry and Fishery Workers	38651	184841	0.209
Craft and Related Trade Workers	546712	8544794	0.064
Plant and Machine Operators and Assemblers	297142	2935281	0.101
Elementary Occupations	311897	1013767	0.308
Average by occupation	717649	3686176	0.195

Source: SPE, GEIH-DANE, authors calculations.

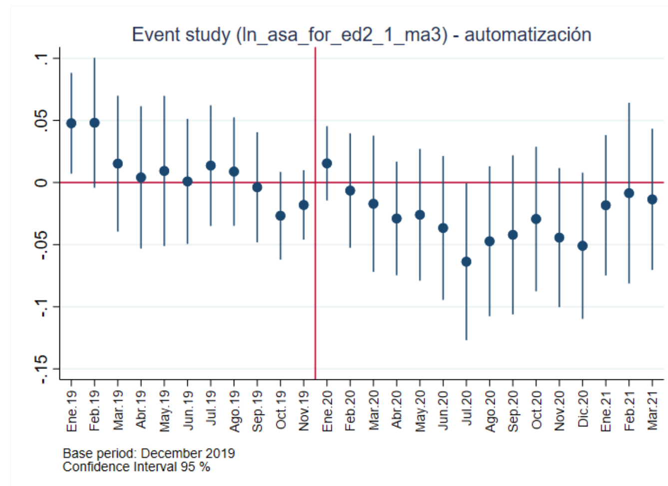
Appendix B: Heterogeneous effects by age, gender, and education for salaried formal workers

Figure B1: differential effects by age

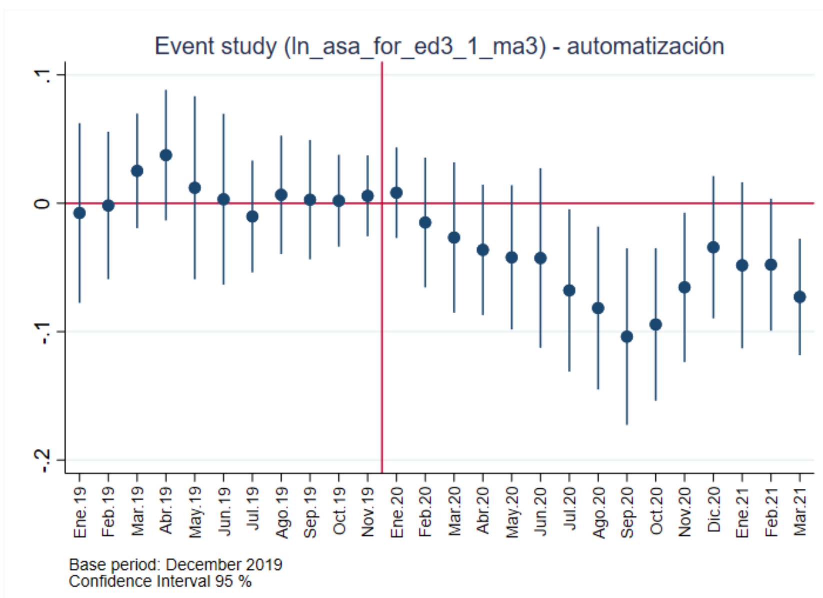
Panel A. Under 25



Panel B. 25-40



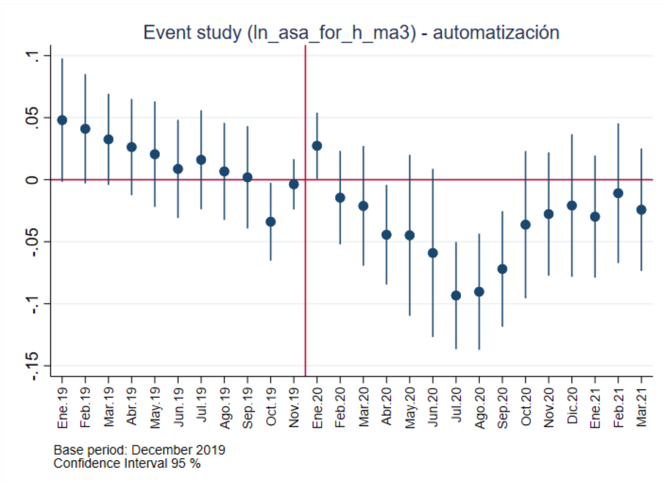
Panel C. Over 40



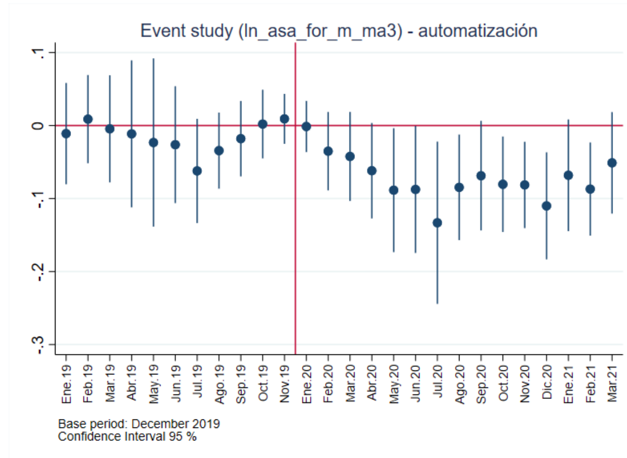
Source: SPE, GEIH-DANE, authors calculations.

Figure B2: Differential effects by gender

Panel A. Male



Panel B. Female



Source: SPE, GEIH-DANE, authors calculations.