Is the Covid-19 Pandemic Fast-Tracking Automation in Developing Countries? Evidence from Colombia

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Abstract

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This paper assesses whether the Covid-19 pandemic accelerated automation in developing countries. We studied the case of Colombia, a country with low R&D and productivity and with high labor informality and unemployment. We estimated event-study models to assess the differential effect of the pandemic on job openings and salaried employment by the potential degree of automation of each occupation. Our results suggest that both vacancies and salaried employment fell more in highly automatable occupations during the pandemic and have since experienced a slower recovery. The effect of the pandemic on automation is mostly driven by sectors that were affected by mobility restrictions. We also found heterogeneous effects by age and gender. The acceleration of automation is mainly affecting the labor market for females and individuals over the age of 40. Finally, we explored the differential effect on occupations with wages around the minimum wage. We found that occupations with wages close to the minimum wage exhibit the highest effect, especially at the onset of the pandemic.

JEL *Classification*: J23, O30, J60

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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 (Autor, et al, 2003, Blanas et al., 2019). However, the evolution of technological progress suggests that even the least-routine jobs can eventually be automated (Brynjolfsson and McAfee, 2014; Frey and Osborne, 2017). The evidence from developed economies suggests a long-term equilibrium between automation and employment (Acemoglu and Restrepo, 2018 a, b; Autor, 2015), but it remains unclear whether this is also the case for developing countries. In general, the automation process replaces less qualified jobs and creates more qualified jobs (Autor, 2013), which increases the relative wages of qualified jobs (Acemoglu and Restrepo, 2018c; Autor, 2015), thus contributing to higher wage inequality (Prettner and Bloom, 2020; Prettner and Strulik, 2020).

Recent evidence suggests that pandemics, particularly the Covid-19 crisis, tend to accelerate the process of automation in developed economies (Chernoff and Warman, 2020, Dolado et al. 2020, Ling and Sáenz, 2020, Saadi and Yoo, 2021). This paper assesses whether this is also happening in Colombia, a developing country characterized by a combination of low investment in R&D (Research and Development) and productivity with high levels of labor informality and unemployment. Specifically, we estimated event-study models to assess the differential impact of the pandemic on labor demand in occupations that are more or less prone to automation. The demand for new jobs during the pandemic was measured using vacancies by occupations collected by the Colombian Public Employment Services Bureau (SPE). We also measured salaried employment using household surveys (GEIH). The probability of automation of each occupation was measured using the Frey and Osborne (2017) and Nedelkoska and Quintini (2018) methodology adapted to the Colombian context.

Our results suggest that, during the pandemic, job openings fell more drastically in occupations with higher potential of automation. These effects are sizable and persistent, with significant coefficients until our last observation (August 2021). We also found negative and significant effects on employment, particularly salaried employment, measured with household surveys. We then explored the extent to which the impact on automatable occupations was larger in sectors that were more affected by mobility restrictions. We found that most of the estimated effects were driven by these sectors. Therefore, mobility restrictions amplified the effect of the pandemic on automation. These results are robust even when controlling for sectorial trends or when using alternative measures of potential automation.

In our last set of results, we showed that automation process has differential effects on workers depending on their age and gender. For salaried workers, we found that the negative effects on employment were mostly driven by the impact on workers over 40 years of age, for whom the gap between more and less automatable occupations was the largest and more persistent since March 2020. In terms of gender, we found that automation affected the labor market of female workers more severely and persistently, especially at the onset of the pandemic (with an estimated effect almost twice as large for females compared to males). However, at the end of the timeframe, the effect was similar to the one found for men. Finally, we explored the differential effect of the automation on worker´s productivity, using the proximity to the minimum wage as a proxy for it. We found that occupations with wages close to the minimum wage exhibited a higher effect than occupations that earn more than the minimum wage, especially at the beginning of the pandemic.

Our paper contributes to the recent literature on the impact of pandemics on automation. Some authors show that the adoption of robots tended to pace up during a pandemic. Consistently, short-term results based on the Covid-19 pandemic show that occupations prone to automation experienced larger job losses and slower recovery, especially for low-skilled occupations in countries such as the United States and the United Kingdom (Saadi and Yoo, 2021; Dolado et al., 2020; Ling and Sáenz, 2020). By demographic groups, women with low levels of education and wages exhibit a high potential degree of automation and risk of viral infection in their occupations (Chernoff and Warman, 2020). The only study assessing an effect of this kind focusing on a developing country is Egaña del Sol et al (2021). Their findings, based on Chilean data, show that job recovery has been considerably slower in sectors with a greater availability of technologies that facilitate automation. Overall, our results confirm that pandemics can accelerate automation, even in economies with low R&D and productivity and high levels of labor informality and unemployment. In addition to this, we were able to show that, in the case of the Covid-19 pandemic, the effect was amplified by the mobility restrictions enacted to prevent the spread of the virus.

This paper is organized as follows. Following the introduction, Section 2 presents the conceptual framework for automation. Section 3 describes the Colombian labor market and comments on the evolution of investment in machinery and equipment and R&D during the pandemic. Section 4 describes the data and empirical strategy used. Section 5 presents the results and includes different robustness checks. Finally, our conclusions are presented in the last section.

2. Conceptual Framework

We based our 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),[2] in which innovation replaces tasks that were previously performed by workers with robots (automation), and creates new tasks whose labor has a comparative advantage.[3] This model suggests that if there is an increase in the cost of labor relative to capital (as we believe it happened during the Covid-19 pandemic), then more tasks can be performed by robots.

The model assumes that each task is performed by a combination of labor and capital, with a specific intermediate task. There is a technological constraint on automation, such that tasks $i \leq I$ are technologically automated (i.e., they are feasible to be produced with capital); however, whether they are produced with capital or labor depends on relative factor prices. Tasks $i > I$ are not technologically automated, and they should be produced only 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:

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

[3] The simple version of the model assumes that capital is fixed and exogenous. 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.

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

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 affected the optimal allocation of tasks through a sudden increase in the labor cost relative to capital[4]. On the one hand, governments put in place strict mobility restrictions, which considerably reduced labor supply in most industries, thus increasing its relative cost[5]. On the other hand, the fear of contagion also raised the opportunity cost of workers further, increasing the relative price of labor.[6] These mechanisms were reinforced by the growing uncertainty regarding both the duration of the pandemic and labor productivity, boosting incentives for automation (Bloom and Prettner, 2020; Leduc and Liu, 2020). Since both the pandemic and mobility restrictions were likely to affect shadow prices, average wages might only partially reflect the changes in the relative cost of labor. As an alternative approach, this paper estimated the differential impact of the pandemic on labor demand by the technological potential of automation of each occupation. Higher than

[4] More generally, empirical evidence for developed economies suggests that during recessions (where the relative price of labor changes) there is an accelerated routine-biased technological change (see Hershbein and Kahn, 2018, for the case of the Great Recession). Jaimovich and Siu (2020) show that over the past 35 years, almost all losses in routine occupations occurred during economic downturns. Moreover, Blanas et al (2019) show for 10 high-income countries that software and robots reduced the demand for low- and medium skill workers, during the period 1982-2005

[5] Additionally, in countries such as United Kingdom and United States there is evidence of an increase on the retirement of older workers during the pandemic (Pizinelli and Shibata, 2022).

[6] In contact-intensive sectors such as hospitality and tourism or health, the adoption of robots started to pace up 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, robotics, information and communication technologies and artificial intelligence were incredibly useful in fighting the pandemic, as well as in alleviating its economic consequences.

proportional job losses on occupations that are more prone to automation would reflect that the pandemic is accelerating automation[7]. On the contrary, no differences between occupations would suggest that the automation process is unaltered by the crisis. This automation process for a middle-income country like Colombia, with low investment in human capital and high informality, might have a persistent effect on unemployment if it is not followed by a permanent and relevant training process.

3. Labor Market and Investment during the Pandemic

3.1 Labor Market

As in many other countries, the Covid-19 pandemic triggered massive economic turmoil in Colombia, bringing about 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 7.0 percent in 2020, the economy's largest decline in its modern history. The contraction in employment was even larger, 11 percent in 2020, and it 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 August 2021, the national unemployment rate was still around 4 pp higher compared to the period before the pandemic, with a worse picture for the urban unemployment rate. A similar behavior was shown by the informality rate, which presented an important increase during the first year of the pandemic (with levels increasing up to 50%), although with a small recovery during 2021.

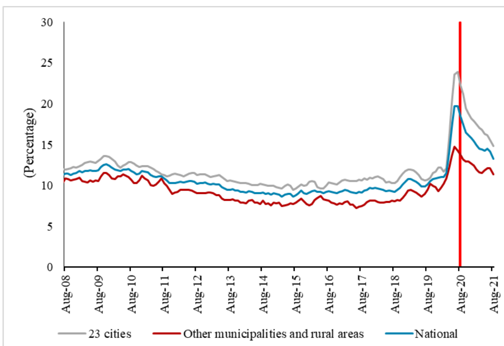
The impact of Covid-19 on employment was the result of a mixture of different forces that interacted simultaneously once the pandemic broke out in March 2020. The main causes included: (i) the individuals' responses to the presence and propagation of the disease (e.g., behavioral changes that shifted 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 hit the whole economy (e.g., disruption of supply chains, reduction of income from international trade and remittances, increase in the volatility

[7] In the Leduc and Liu (2020) model, uncertainty also affects aggregate demand and new investments in automation. The net effect depends on the size of the two forces. Their calibration for the US shows that the technology-shifting effect dominates the reduction on labor demand, increasing the automation probability when productivity uncertainty rises. Therefore, the option of automation enables firms to mitigate the adverse impact of uncertainty. These results are robust to assuming that firms can directly automate an existing job, as our empirical findings suggest.

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 (2022) present a decomposition of the contribution of each of the latter sets of causes in the Colombian labor market outcomes.

Figure 1

Panel A:
Unemployment Rate



Panel B:
Informality Rate
twenty-three cities

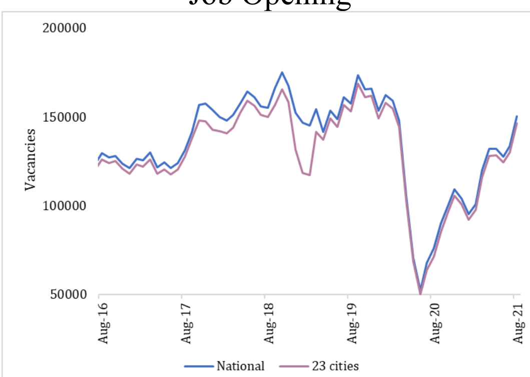
Source: seasonally adjusted series, three-month moving average
GEIH-DANE, authors' calculations.

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 25-year-old individuals or younger fell 16 percent, versus 10 percent of individuals in other age groups (Bonilla et al, 2021b). Third, due to the nature of the crisis, job losses were largely heterogeneous across sectors and, even within sectors, job destruction was disproportionally larger for smaller and less productive firms (Morales et al, 2022; Bonilla et al, 2020).

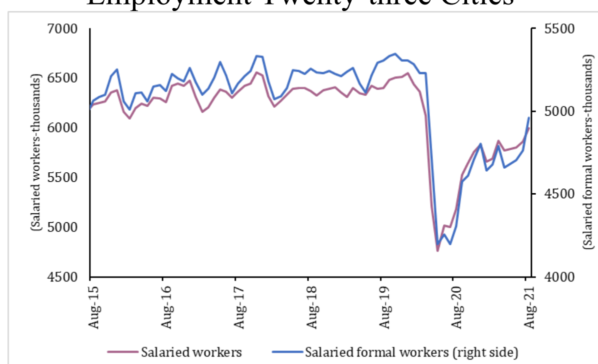
Regarding job offers, we present the evolution of total online job openings during the pandemic in **Figure 2**. Job openings declined 70 percent in April 2020 relative to January 2020. Since May, vacancies started to recover slowly and in August 2021, job openings had levels similar to before the pandemic (Panel A of Figure 2). As for the level of employment (salaried and formal salaried workers), there was also a significant decline between March and June of 2020; however, after the shock, the recovery has been slow and the levels of total employment are still below their pre-pandemic counterparts (Panel B, of Figure 2). When disaggregated by occupations, we see that, in general, most of the vacancies come from service and sales activities, clerical support, and professional occupations. However, there were large composition changes in occupations between 2019 and 2020-2021. Particularly, the share of vacancies for both professional and technical jobs exhibited significant gains in 2020 and 2021, whereas those from sales, clerical support, and elementary occupations experienced considerable losses (Panel C of Figure 2). These compositional changes are signs of a shift in the relative demand for labor, for which we found evidence that can be linked to the attributes of different occupations (see section 4).

Figure 2

Panel A:
Job Opening



Panel B:
Employment Twenty-three Cities



Panel C
Job Openings by Occupations

Note: *composition in 2021 correspond to January-August 2021

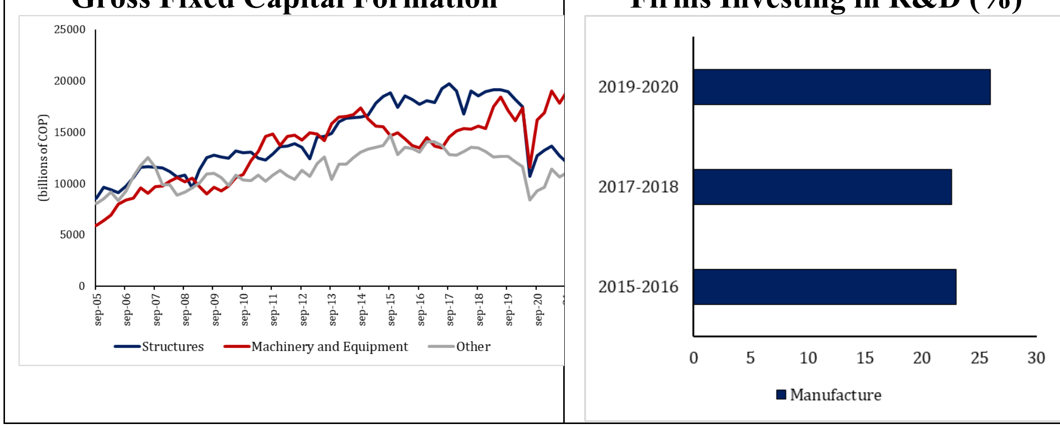
Source: Seasonally adjusted series, three-month moving average
GEIH-DANE, SPE, authors' calculations.

3.2 Investment in Machinery and Equipment and in R&D

The negative and persistent effect of the pandemic on employment contrasts with a quick recovery of investment in machinery and equipment, as recorded in the national accounts. As can be seen in **Figure 3, Panel A,** gross fixed capital formation contracted during the two first quarters of the pandemic, when strict lockdowns were imposed. However, the recovery after this period was fast, particularly for machinery and equipment. There is also evidence of an increase in R&D investment in 2019-2020. **Figure 3, Panel B** shows the share of manufacturing firms that invest in R&D based on the Survey of R&D from the National Department of Statistics (DANE).[8] As seen, there was an important increase in the proportion of firms that declared to invest in R&D compared to the two last waves (2015-2016 and 2017-2018). Finally, **Figure 3, Panel C** shows the evolution of imports that can be potentially related with the automation process. As may be observed, after March 2020, this measure exhibited an increasing trend, especially in tons.[9]

Figure 3

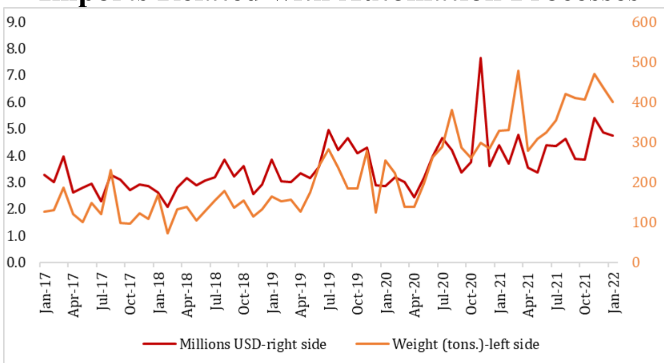
Panel A: Gross Fixed Capital Formation | **Panel B: Firms Investing in R&D (%)**



[8] The survey is applied bi-annually to 7,000 companies from the Annual Manufacture Survey (AMS) since 2006.

[9] We measure imports related with automation process in Colombia using all imported 6-codes which can be related with robots or automation, such as: 842389, 842870, 842890, 844316, 844330, 847950, 847989, 848180, 851521, 851531, 851580. This methodology is similar to Dixon (2020) for building the number robots in Canada.

Panel C
Imports Related with Automation Processes



Source: National Accounts, Imports Data, DANE- R&D Survey, authors' calculations.

Although granular information remains scarce, these trends suggest that investment in both machinery and equipment, imports related with the automation process, and R&D increased during the pandemic in Colombia. This could reflect a potential evidence of labor substitution for capital, which would be consistent with an acceleration of automation.

4. Data and Empirical Strategy

4.1 Data

We characterized the evolution of the Colombian labor market by using two main sources of information: (i) online job vacancies posted by SPE, and (ii) measures of formal employment from household surveys (GEIH) collected by DANE. The SPE is an administrative unit created in 2013 and assigned to 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.[10] Job openings can be posted with the intention of either replacing a worker that has

[10] 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.

been separated from the firm or filling new jobs created by firms; however, we cannot distinguish between these two possibilities, so we used both types of offers interchangeably, and we will refer to them simply as vacancies[11]. The occupations we considered 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 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 National Classification of Occupations (CNO-70). We created a crosswalk between this classification and the 1-digit ISCO 08 adapted for Colombia used by SPE. We then aggregated monthly employment by occupation and city, which will be our unit of observation. We focused on salaried workers and formal salaried workers.[12]

Panel A of Table B1 in Appendix B displays summary statistics of the total number of annual job-posting offers collected by the SPE in the period 2015 to 2020, suggesting that, in average, around 1.2 million vacancies are posted yearly in the main 23 cities of the country. To assess how representative this data is, we computed the annual amount of hires in the formal and salaried segments of the same cities implicit in the records of the GEIH[13]. We found that, in this segment, the survey estimates that there are approximately 6.6 million hires, on average, per year. So, if all vacancies were filled, the mechanism of job postings in the SPE would be facilitating, on average, around 20 percent of all the hires in the urban salaried labor market, a proportion that is increasing over time.[14]

We measured the probability of automation for each occupation in Colombia following Nedelkoska and Quintini (2018), who in turn built on Frey and Osborne (2017).

[11] The vacancy posted in the SPE has an average duration of 1.5 months, taking into account the posted date and the expired date suggested by the firm (Cardozo, 2019).
[12] Formal workers report contributing to the Colombian social security system.
[13] 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.
[14] 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 A 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.

Thus, we estimated 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[15]. In our case, the training data corresponds to individuals in all OCDE countries, in occupations that matched the 70 occupations classified by Frey and Osborne (2017) by their automation potential. The explanatory variables are the same as in Nedelkoska and Quintini (2018) who use a set of questions related to finger dexterity, the ability to solve simple and complex problems, and the requirement for teaching, advice, and negotiation, among others, in order to capture the bottlenecks identified by Frey and Osborne (2017)[16]. The estimated coefficients were applied to the remaining individuals in the data. Thus, we obtained a prediction of the automation potential for all occupations (4-digit ISCO08 codes).

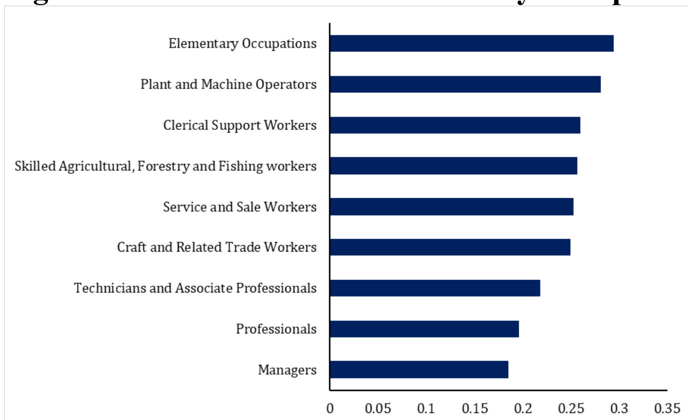
At this point, because the automation potential varies across individuals in OECD countries, we adapted this probability to the Colombian standards. First, we averaged the probability for each occupation at 2-digit ISCO08 level (to account by the adaptation process of technology in Colombia this average is obtained by weighting the participation of each OECD country in the Colombian imports); then the probability was standardized, resulting in an index for automation at 2-digit ISCO08 level. Secondly, we matched the automation index (at 2-digit ISCO08) with the GEIH data at individual level. Finally, we averaged the index for each city and each occupation at the 1-digit ISCO08 level. This average was weighted by using the GEIH individual expansion factors to account for the composition of the Colombian labor market, thus causing the automation potential to vary across city and occupation.

Figure 4 presents the probability of automation for each occupation in our sample. As expected, occupations with a higher probability of being automatable are those with a low level of competence, such as elementary occupations and machine operators. Notice that this measure was constructed using information on the type of tasks performed at the different occupations/jobs before the pandemic. Thus, for our study, the variable is predetermined and, by construction, is completely exogenous to the shock caused by the pandemic.

[15] By the time of the PIAAC was conducted Colombia was not part of the OECD.

[16] The bottlenecks refer to a group of human abilities that, in the actual state of the automation frontier, can´t be easily replaced. Fray and Osborne (2017) listed them as: perception-manipulation, creative intelligence, and social intelligence.

Figure 4: Likelihood of Automation by Occupation



Source: Authors' calculations.

4.2 Empirical Strategy

We assessed whether the pandemic had a differential impact on the demand of occupations that are prone to automation by using a panel event study design with a monthly frequency. This methodology is a generalized extension of differences-in-differences or two-way fixed effect models (Clarke and Tapia-Schythe, 2021). We regressed job-posting vacancies collected by the SPE (or the level of salaried employment from GEIH in the second specification) as a function of the automation variable. The estimated equation can be represented as:

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

We interacted the automation variable with monthly dummy variables (D_τ) for the post-pandemic period: from January 2020 to August 2021. 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 controlled for individual effects for each combination of city-occupation (δ_{jc}) and for monthly fixed effects (δ_t). The model also controlled for disease propagation at each city θ_{ct} (measured as the number of deaths per million people of working age), where ε_{jct} is an unobserved error term[17].

This design allowed us to test whether there were systematic differences at the automation margin before the declaration of the pandemic. In addition, the design allows us to assess whether the pandemic was responsible for an increase in these differences. 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 or any other aggregate shock. To overcome this difficulty, we controlled for time-fixed effects. Furthermore, as we will show in the next section, we found no evidence of pre-trends, which suggests that occupations with high probability of automation exhibited similar trends in job vacancies (or salaried employment) before the pandemic. Following Bertrand, Duflo, and Mullainathan (2004), we clustered the error terms by occupation and cities to address the serial correlation problem[18].

5. Results

We assessed the differential effects of the pandemic on occupations that are prone to automation. We based 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 estimated the heterogeneous effects by age and gender. Finally, we assessed 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.

[17] This parameter can also capture any potential disruption on the labor supply given by the exposition of the disease, that may affect the probability of firm´s to fill a vacancy. However, after the pandemic, we see than the number of people searching for a job increased more in occupations with a high probability of automation. Therefore, it is unlikely that the difficulty to fill a vacancy is driving automation.

[18] This correction works well when the number of groups is large (in our case there are 10*23=207 groups). See also literature related such as: Clarke and Tapia-Schythe (2021), Angrist and Pischke, (2008), Cameron and Miller (2015); Mackinnon and Webb (2017), among others.

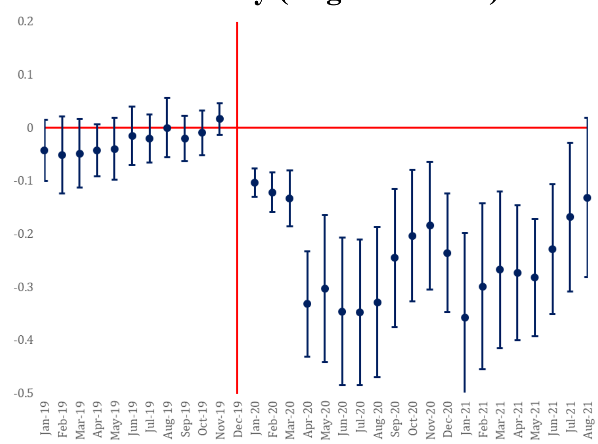
5.1. Automation, Job Posting, and Employment

We began our analysis by estimating the differential effects of the pandemic by the likelihood of automation on new job vacancies in **Figure 5**. This measure reflects the demand for new formal jobs, and is therefore related with the more formal segment of the economy. The first result to highlight is that we found no evidence of pre-trends, which suggests that occupations with high probability of automation exhibit similar trends in job vacancies before the pandemic began.

We found that, as early as January 2020, automatable occupations were losing vacancies more rapidly than the rest, suggesting a quick adjustment process of the country's relative labor demand. Between January and March, the estimated differential effect was near -0.13 pp (percentage points), which implies that occupations that are more likely to be automatable (those which have an automation index one standard deviation above the average) exhibited an additional reduction on the job posting vacancies, when the first announcements of a public health emergency were released by the WHO.

Figure 5

Event study (Log-Vacancies)



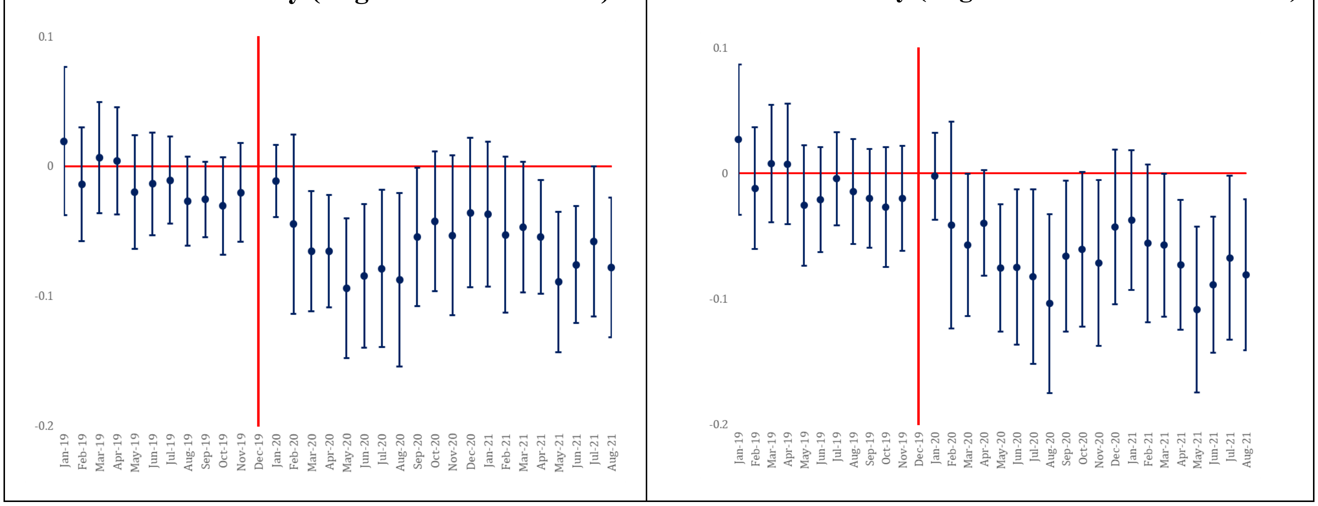
Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the job posting vacancies on occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: SPE, GEIH-DANE, authors' calculations.

The gap between occupations that are more and less susceptible to automation widened considerably in April, when the sanitary emergency was declared and the national lockdown was enacted. The estimated differential effects oscillated around -0.35pp until August, when the lockdown measures begin to relax. After this, the gap closed for some months, with a minimum difference of -0.2 pp in November. In December, the country was hit by a second wave of contagion, and the differences started to grow again, reaching a new maximum close to -0.4 pp in January 2021 and a reduction on the impact at the end of 2021. (**Figure 5**).

Results were fairly similar when we used employment measures based on household surveys. **Figure 6** shows the differential effect of the pandemic on total salaried workers (Panel A), and total formal salaried workers (Panel B)[19]. In both cases, we found no significant differences in the pre-treatment period, and negative effects starting February 2020. However, total employment reflects less anticipation than job vacancies, probably because it is the realization of vacancies, as estimates are only statistically significant since March. The largest effects were found between May and August, with estimated effects near 0,1 pp. Since then, the gap has stabilized around 0,05 pp, although with less precise estimates, and became significant again at the end of 2021, with magnitudes around 0,1 pp.

Figure 6

Panel A. Event study (Log-Salaried Workers) | **Panel B. Event study (Log-Salaried Formal Workers)**



Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.

The differences in the results between when using job posting and total employment is that total employment accounted for the stock of jobs, while job posting vacancies captured only (entry) job flows. Thus, vacancies are more sensitive to exogenous events and anticipate

[19] Salaried formal workers refer to those workers who are salaried and also work in firms with more than 5 employees.

the future trend of total employment. Moreover, as we said before, our measure of vacancies has a larger coverage for some segments of salaried works (for example, in high-skill occupations, see Panel A of Table A1 in Appendix), which could explain part of the differential.

In general, our results are in line with Ling and Sáenz (2020) for the United States and with Cruz et al. (2020) for the case of Chile. The latter found that the occupations that present a higher likelihood of automation were also those that recorded a higher fall during the pandemic period. Moreover, as a robustness check, we replaced our metric of automation by the index of both automation and transmission risk proposed by Chernoff and Warman (2020), finding similar results (see Appendix B)[20].

Overall, our findings suggest 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 triggered large, persistent effects on the labor market, permanently reducing the demand for highly automatable occupations. The potential acceleration of the automation process in Colombia calls for a reallocation of human capital towards occupations with higher skills, a process that requires permanent and pertinent investment in human capital.

5.2. The Role of Mobility Restrictions

During the first months of the Covid-19 pandemic, the Colombian government enacted strict mobility restrictions to prevent the spread of the disease. Some economic activities that were classified as essential were excluded from these measures.[21] We explored the role of mobility restrictions estimating separate regressions for occupations that were excluded or not from the government restrictions. **Figure 7** panel A shows the results for occupations without mobility restrictions. In this case, we found that in sectors with no restrictions, there was no differential effect on occupations by the likelihood of automation. However, for the case of

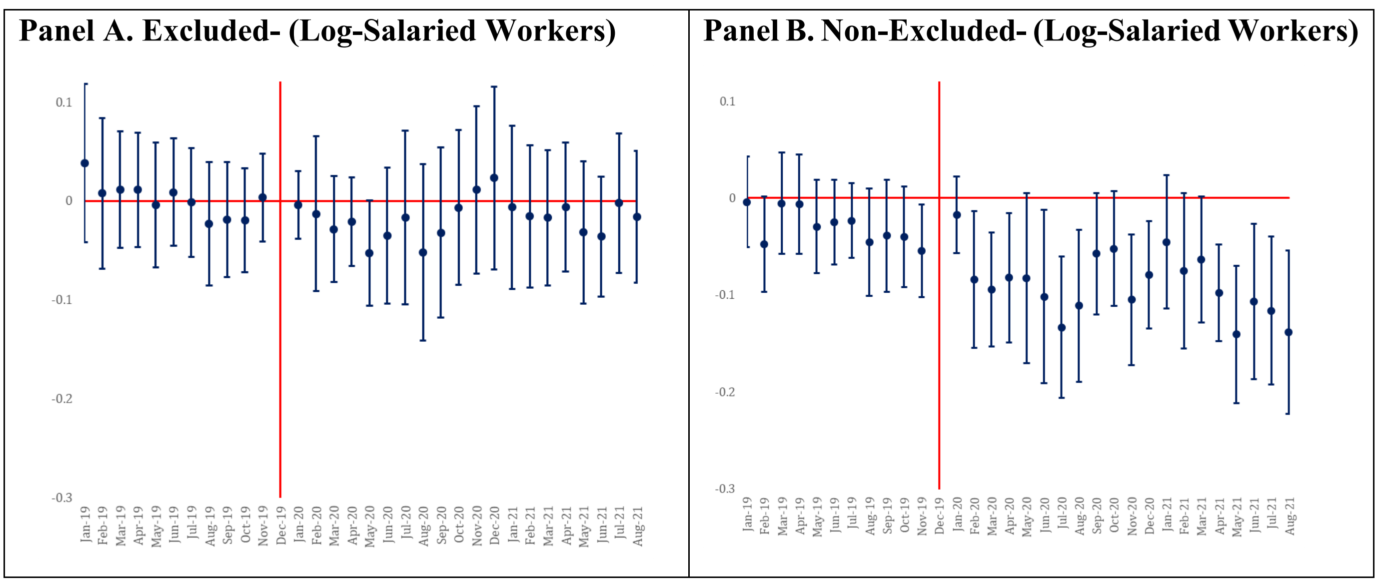
[20] Chernoff and Warman (2020) propose an index that combines the occupations that have a high automation potential and also exhibit a high degree of risk of viral infection for the US.

[21] These essential sectors included public administration, finance, agriculture, and public utilities and the sectors that were part of their supply chains. For a more comprehensive evaluation of the effect of the mobility restrictions on the employment in Colombia see Morales, et al (2022).

occupations located in a sector with mobility restrictions, the differential effect by the likelihood of automation is negative and significant. Moreover, these results are significant for a long period even after the mobility restrictions were eliminated (Panel B, **Figure 7**).

These results are not surprising: as we mentioned before, 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 non-excluded sectors. These sectors may have considered automation as an alternative for compensating the cost of future mobility restrictions as well as a mechanism to control the disease itself. As a robustness check, we also used a specification in which we included the sectoral dimension (excluded and non-excluded) to our units of observation. With this specification, we: i) estimated our main regression by controlling for individual effects for each combination of city-occupation-sector (excluded or non-excluded), (see Panel C1, Appendix C); ii) estimated our main regression controlling for differential time trends in all sectors, which allowed us to account for any possible pre-existing sectorial trend that could also affect our results (see Panel C2, Appendix C). We found our main findings sustained with magnitudes that were similar to our baseline estimations.

Figure 7



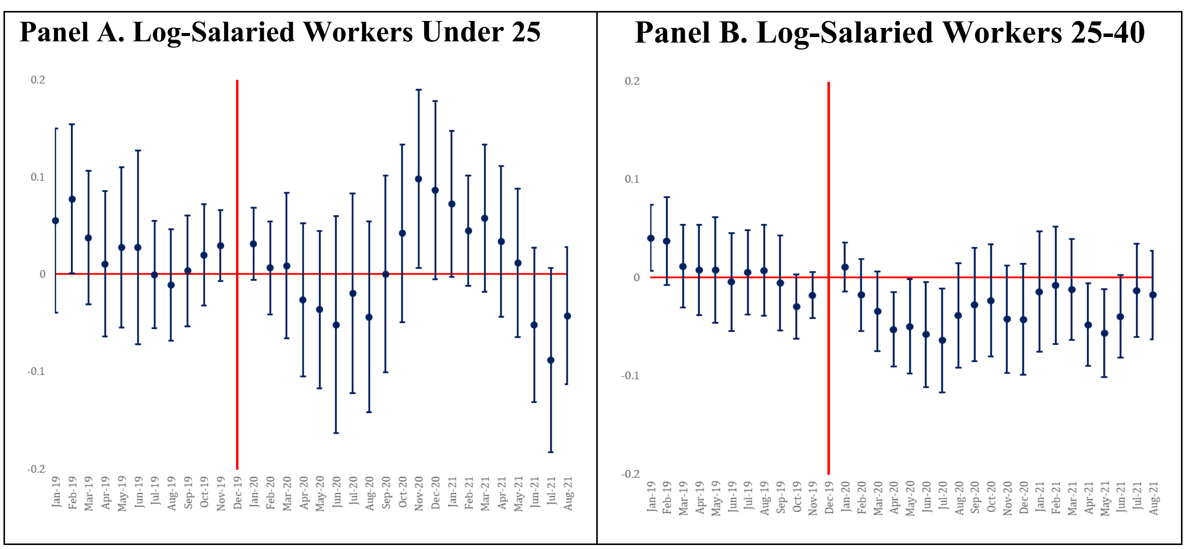
Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.

5.3. Heterogeneous Effects by Age and Gender

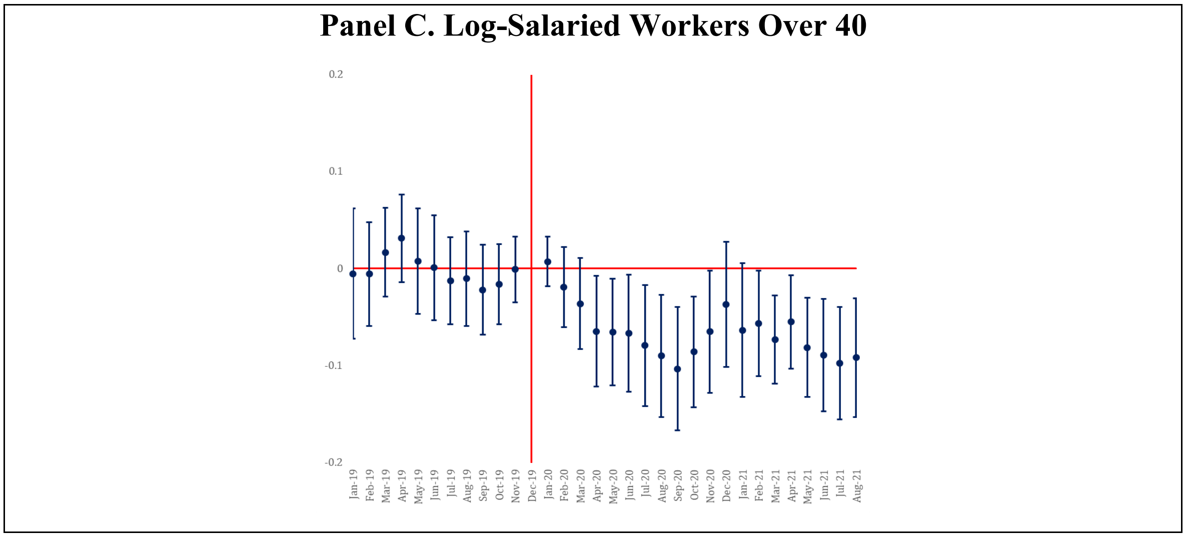
Recent literature has presented heterogeneous effects of the automation process by different levels of skills, with low-skill occupations being at higher risk of being automatable (Chem, 2020; Costa-Dias et al, 2020; and Dolado et al, 2020). Moreover, workers such as women and low-skilled older workers were the most affected during the first year of the pandemic (Garcia-Rojas et al, 2020; and Bonilla et al, 2021a). Therefore, in our context, we explored whether during the pandemic the pace up of the automation process differed between different segments of the labor force by estimating separate regressions by age and gender (using the household survey).[22]

Figure 8 presents the differential effect by age. 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 was reached in September 2020 and at the end of 2021. Adults between 25 and 40 experienced a considerably smaller effect in magnitude and significance converging to zero since January 2021. For workers under 25, we found that the difference was small during the first months of the pandemic and became positive and significant in November 2020, after which it became not significant.

Figure 8



[22] 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. Hence, we cannot explore the heterogeneous effects of automation by these characteristics.

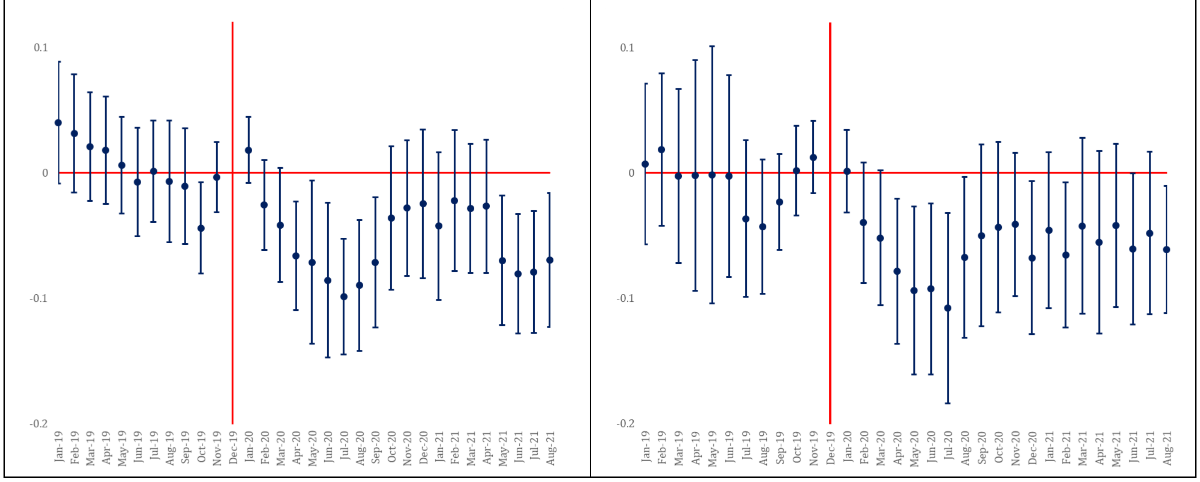


Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.

The difference between genders is subtler. While the estimated coefficients follow a similar pattern, the magnitude of the effects was consistently larger for females (**Figure 9**). This was reflected in a sharper decrease during the first months of the pandemic. The estimated effect is large for females than for males from April to July, but it remained similar at the end of 2021. Therefore, automation affected the labor market of female workers more severely and persistently at the beginning of the pandemic. This effect may have resulted from two facts: first, women were more concentrated in highly automatable occupations (mainly in contact-intensive sectors) at the beginning of the pandemic; and secondly, after losing their jobs, their recovery was largely asymmetric relative to men, with smaller probabilities to return to participate in the labor market (Garcia-Rojas et al, 2020). We also replicated these estimations for salaried-formal jobs, finding similar results (see Appendix D, Figures D1 and D2).

Our findings on the heterogenous effects of automation are aligned with those of Kugler et al. (2020), who studied how the automation process in the US produced job displacement in Colombia from 2011 to 2016. Kugler et al. (2020) also found a negative displacement effects for women, older workers, and workers employed in small- and medium-sized enterprises in Colombia, due to the acceleration of automation in the US.

Figure 9



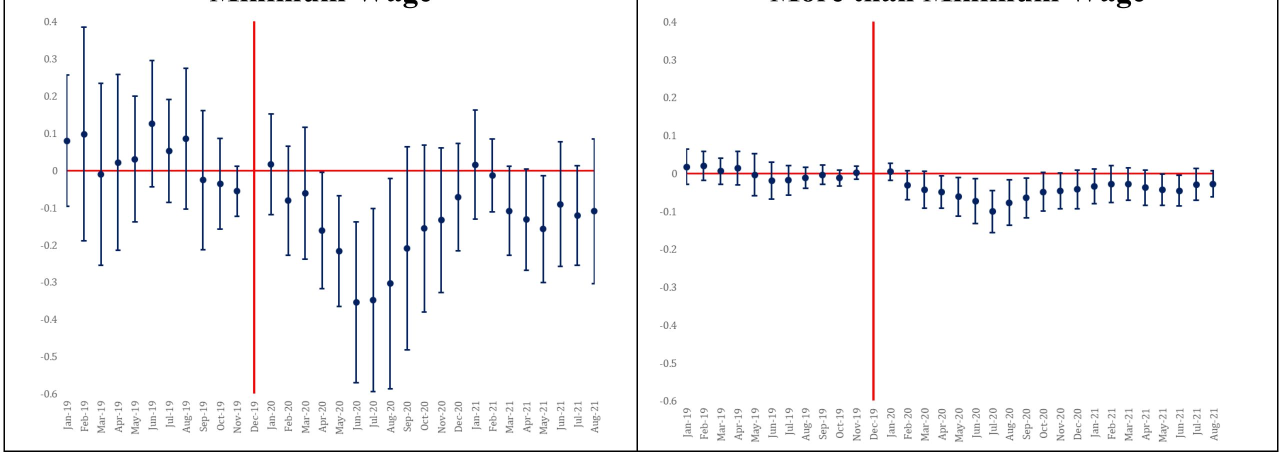
Panel A. Log- Salaried Workers - Male | **Panel B. Log- Salaried Workers-Female**

Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.

5.4. Heterogeneous Effects by Worker´s Productivity

We explored the differential effect of the automation process by the level of workers´ productivity, using the proximity to the minimum wage as a proxy for it. Specifically, we divided salaried workers into two groups based on their wage: those with wages equal or slightly higher than the legal minimum wage, and those with wages that were considerably higher.

Figure 10



Panel A. Log- Salaried Workers Minimum Wage | **Panel B. Log- Salaried Workers More than Minimum Wage**

Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.

Figure 10 shows the results. Occupations with wages close to the minimum wage exhibited a higher effect than occupations earning more than the minimum wage, especially at the beginning of the pandemic (with four-fold magnitudes in the period from April to August 2020). However, the differential effects started to close their gaps at the end of 2020, with non-significant estimates in some months.

6. Conclusions

We estimated event study models to evaluate the differential effect of the pandemic on job openings and total salaried employment according to the potential of automation for different occupations. We found that during the pandemic, there was a significantly lower job opening for occupations with greater potential of automation than for those that are less automatable. These differences are significant and persisted until our last observation, being around -0.2 pp in August 2021. Moreover, when using salaried employment, we found a significant negative difference that started from February 2020 and ended in August 2020 (nearly a 10% difference). However, since then, the gap has stabilized with less precise estimates.

Our results are mostly driven by sectors that were affected by the mobility restrictions that took place during the first months of the pandemic. We found a significant differential effect mainly in sectors with mobility restrictions. These results suggest that 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 offset the cost of future mobility restrictions. These results are robust even when controlling for sectorial trends or when using alternative automation indexes such as the one proposed by Chernoff and Warman (2020).

We also explored whether our results are heterogeneous 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 years of age, we found that the difference was small during the first months of the pandemic and became positive and significant in November 2020, after which it became not significant 2020. In terms of gender, we found that the magnitude of the effects was consistently larger for females at the beginning of the pandemic. This is reflected in a sharper decrease during the first months of the pandemic, where the estimated effect is almost twice as large for females than for males. However, by the end of 2021, the effect tends to be similar between women and men.

Finally, we explored the differential effect of the automation process by the level of worker´s productivity, using the proximity to the minimum wage as a proxy for it. Our results show that occupations with wages close to the minimum wage present a higher effect than occupations than earn more than the minimum wage, especially at the beginning of the pandemic. However, the differential effects started to close their gaps at the end of 2020, with estimates that were non-significant in some months.

The fact that the Covid-19 pandemic accelerated the automation process in Colombia could have long-term effects on the labor market, permanently reducing the demand for highly automatable occupations, for instance. Such a shift on labor demand might imply a reallocation process of human capital that would require permanent and relevant training. In a country with a 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), thus inducing a negative effect on the long-term unemployment rate.

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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

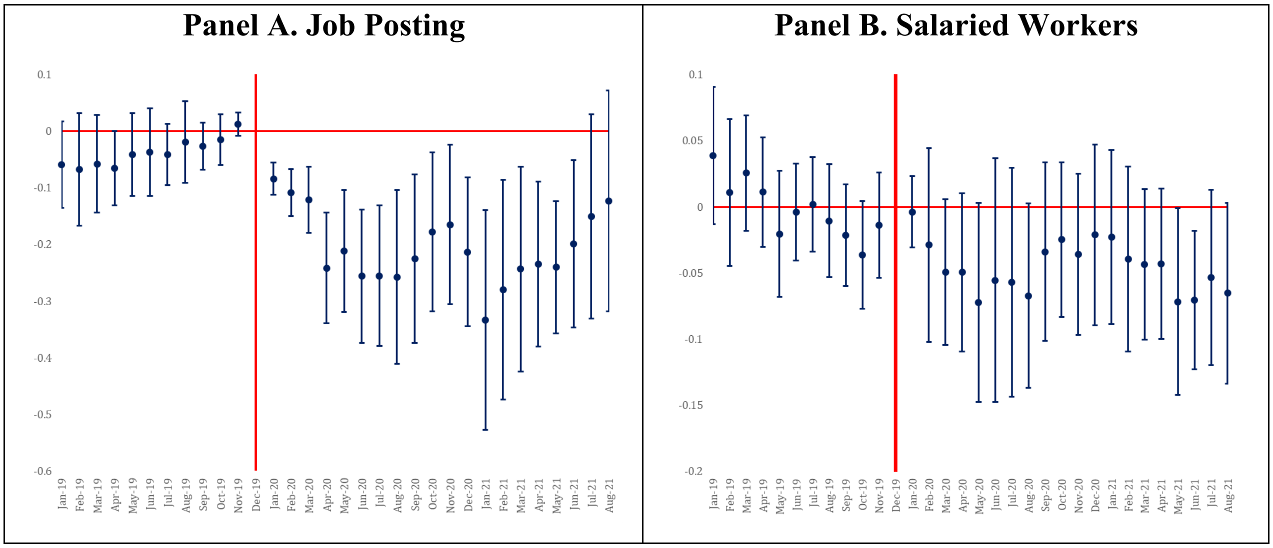
Panel B. Total vacancies 2015-2019

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: Using the Chernoff and Warman (2020) Index

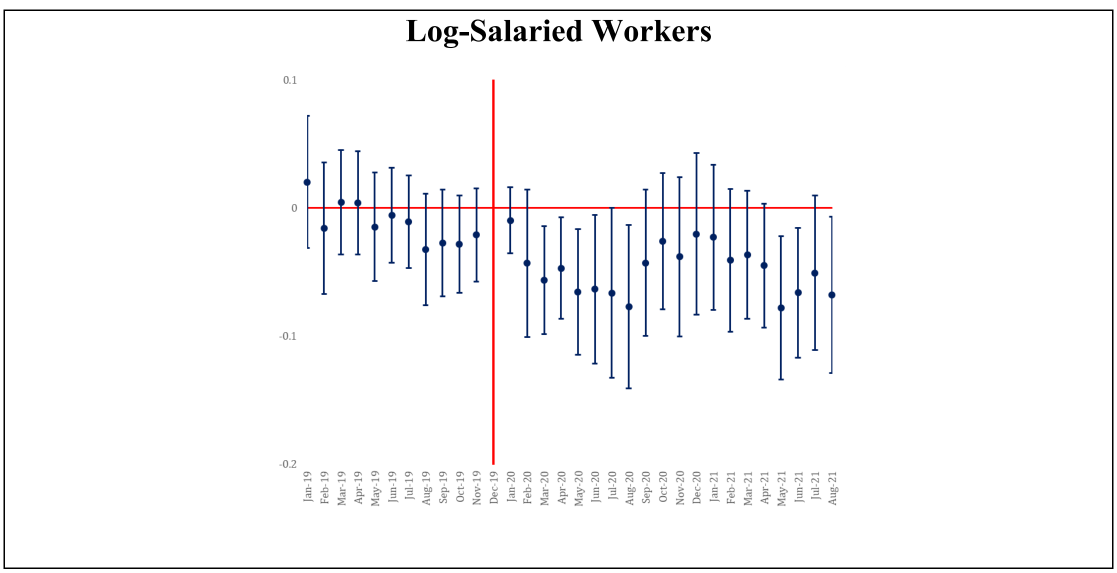
Figure B1



Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the job posting (panel A) or salaried occupations (panel B) that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.

Appendix C:

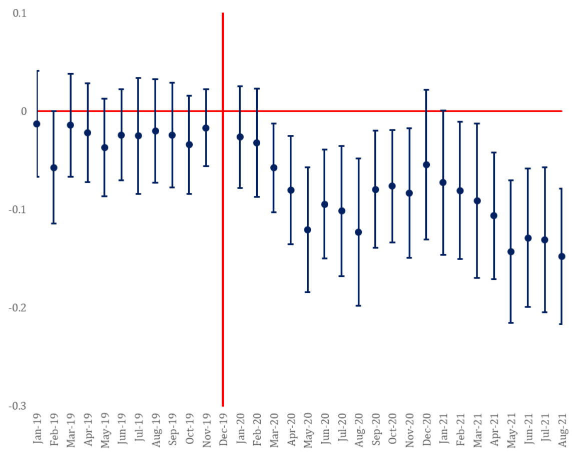
Figure C1: City-Occupations-Excluded and Non-Excluded Sectors



Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level and sector (excluded or not excluded).
Source: GEIH-DANE, authors' calculations.

Figure C2: City-Occupations-Sectors (time trends)

Log- salaried workers

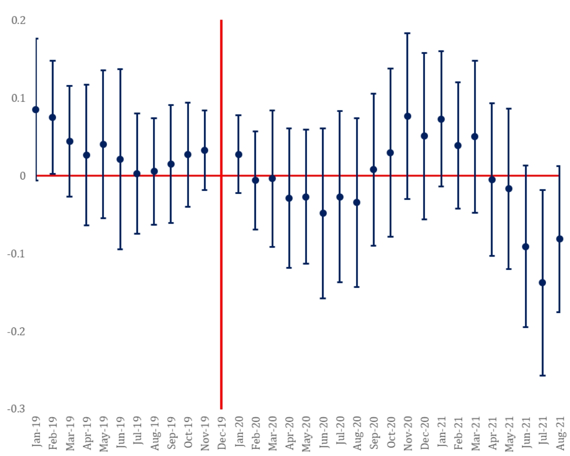


Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation-sectors level.
Source: GEIH-DANE, authors' calculations.

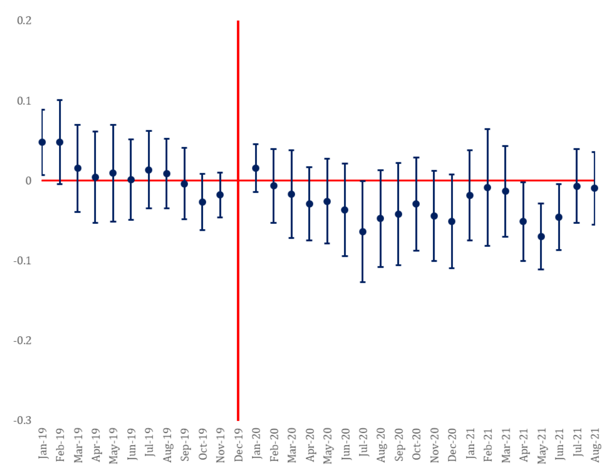
Appendix D: Heterogeneous Effects by Age, Gender, and Education for Salaried Formal Workers

Figure D1: Differential Effects by Age

Panel A. Log- Salaried Formal workers Under 25

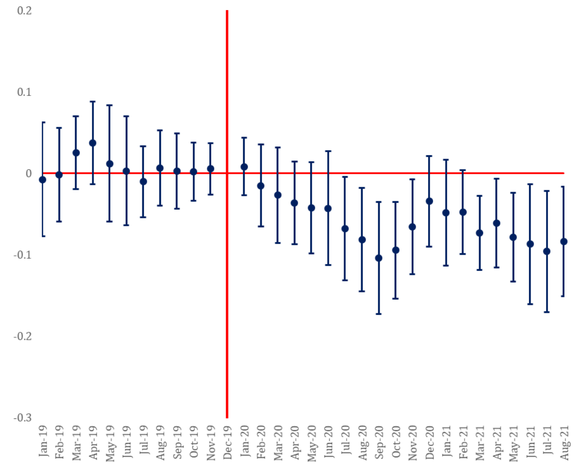


Panel B. Log- Salaried Formal Workers Between 25-40 years' old



Panel C. Log- Salaried Formal Workers

Over 40 years' old

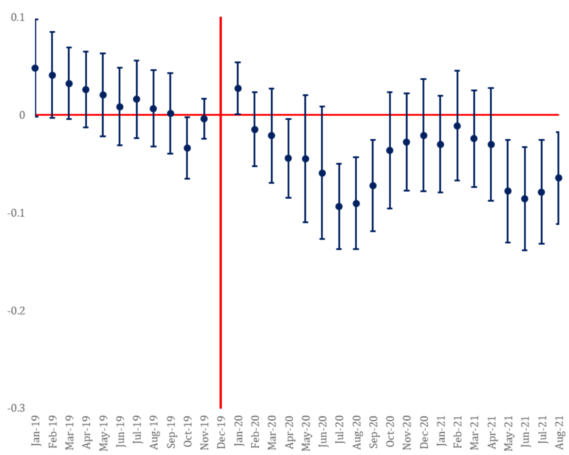


Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the formal salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.

Figure D2: Differential Effects by Gender

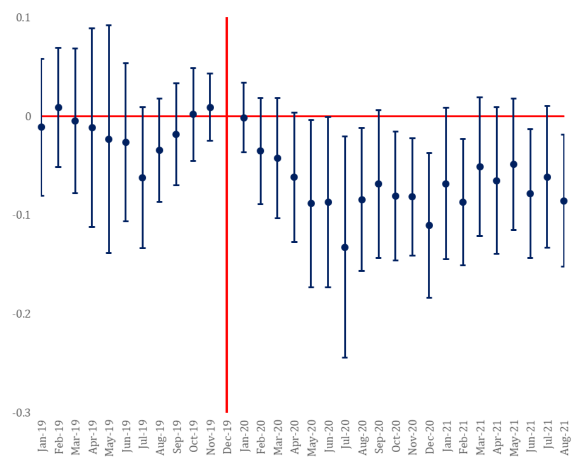
Panel A. Log- Salaried Formal Workers

Male



Panel B. Log- Salaried Formal Workers

Female



Note: Base period: December 2019 – Confidence interval 95%. Each monthly coefficient indicates the estimated additional reduction (pp) on the formal salaried occupations that are more prone to automation compared to those that are less automated. The errors are clustered at city-occupation level.
Source: GEIH-DANE, authors' calculations.