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Evidence from Peru's Labor Market

Miguel Benítez-Rueda
Nicolás Domínguez
Eric Parrado

Inter-American Development Bank
Department of Research and Chief Economist

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Miguel Benítez-Rueda*
Nicolás Domínguez**
Eric Parrado*

* Inter-American Development Bank
** New York University

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Abstract*

Mobility restrictions have the potential to accelerate automation. Using difference-in-differences and triple-differences empirical strategies, and leveraging cross-industry variation in mobility restrictions and within-industry variations in automation risk, this paper estimates the impact of pandemic-related restrictions on automation in Peru. Our results indicate that mobility restrictions significantly decreased employment rates (−22.5%) and hourly wages (−74.1%) for workers in highly automatable jobs up to 18 months after the shock. These effects were particularly pronounced among women, small and medium-sized firms, informal workers, and individuals with low and medium skill levels working in manufacturing, construction, and services. Evidence suggests that occupational mobility from high-risk to low-risk jobs drove recovery afterwards.

JEL classifications: J21, J46, J62, O33

Keywords: Automation, Mobility restrictions, Labor markets, Occupational mobility, Jobs

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1 Introduction

The recent surge of new technologies—including computational algorithms, robots, and artificial intelligence—is reshaping the modern economy and paving the way for automation. While the impact of technological change on labor markets has been extensively studied in the developed world (for example, Autor et al., 2003; Goos and Manning, 2007; Acemoglu and Restrepo, 2020), the evidence is less conclusive for developing economies, where technology adoption is constrained by limited access to credit, infrastructure barriers (Foster and Rosenzweig, 2010), and lower labor costs, especially in the presence of large informal labor markets. Some studies find null or modest links to employment and wages (De Vries et al., 2020; Novella et al., 2023), while others find a decline in jobs that are more vulnerable to automation (Gasparini et al., 2021; Brambilla et al., 2022).[1]

Given this mixed evidence, this paper investigates whether exogenous shocks that limit labor mobility can be a turning point for automation in the developing world. More specifically, we examine the impact of COVID-19-related policy responses, which imposed unprecedented constraints on firms, workers' mobility, and in-person interactions. We focus on Peru, a highly informal developing economy, and leverage a detailed longitudinal labor survey that tracks individuals for up to five years.

Pandemic-related mobility restrictions can be interpreted as a sudden and exogenous increase in labor costs (Bonilla-Mejía et al., 2022), which can increase the returns to adopting technology and automating jobs. For instance, according to a World Economic Forum (2020) survey, after the pandemic broke out, around 50% of business leaders were set to accelerate the automation of jobs in their companies, and 43% of businesses indicated that they were set to reduce their workforce because of technology integration.

Evidence on the implications of COVID-19 restrictions on automation is scarce, both for developed and developing countries. For the US, Ding and Molina (2020) and Chernoff and

[1] Other studies suggest that high-income countries' technology adoption is spreading automation to developing labor markets through reshoring rather than through direct technology adoption (Kugler et al., 2020; Artuc et al., 2019)

Warman (2022) suggest that workers at higher risk of automation were more vulnerable to the COVID-19 shock. For Chile, a developing economy, Egana-delSol et al. (2022) find that the outbreak of the pandemic reduced employment in occupations more prone to automation at the industry level, though they do not differentiate between paralyzed and essential jobs. Additionally, Bonilla-Mejía et al. (2022) find that the pandemic reduced job openings and employment in highly automatable occupations in Colombia, using occupation-city-level data.

Our approach offers several advantages compared to previous studies in several dimensions. First, we rely on individual-level data, which allows us to track the same workers over time and determine whether they lose their jobs after the shock. In contrast, industry- and occupation-level data fail to reveal whether individuals lose their jobs or whether they switch to another industry or occupation. This limitation hinders researchers' ability to identify whether the job-volume reduction is genuinely impacting individuals' outcomes. Moreover, using individual-level data enables us to account for individual-specific factors that may affect the likelihood of exposure to mobility restrictions and automation, and it allows us to compare individuals within the same industry, region, and time period but in occupations subject to different levels of automation risk.

Second, our empirical strategy allows us to better disentangle the automation effect from the paralyzation effect. We employ a combination of difference-in-differences and triple-differences methods, leveraging the timing of the COVID-19 shock, policy-induced mobility restrictions imposed on certain industries, and within-industry variation in automation risk to estimate the impact of pandemic restrictions on automation.

Our findings reveal that workers in paralyzed activities who were previously employed in highly automatable jobs, experienced a significant and sustained drop in employment and wages as a result of pandemic-related restrictions. Additionally, our study highlights that job recovery for these individuals was mainly driven by their ability to transition into low-risk occupations. We show that these effects were particularly pronounced for women; informal workers; manufacturing, construction, and services workers; individuals with medium and low skill levels; and workers in small and medium-sized enterprises.

This paper is organized as follows. Section 2 details the data used and discusses alternative measures of the risk of job automation. Section 3 presents our empirical strategy for measuring the impact of pandemic-related mobility restrictions on labor automation in Peru. Section 4 presents the main results, several robustness checks, and heterogeneous effects. Finally, section 5 concludes.

2 Data

This study draws on data from multiple sources: (i) the Peruvian National Household Survey (ENAHO), (ii) the Ministry of Labor's classification of essential industries, and (iii) the OECD Programme for the International Assessment of Adult Competencies.

ENAHO collects quarterly data on several labor-market and socio-demographic variables, including employment, wages, occupation, and industry. It uses a rotating sample design that allows for tracking the same individuals once every year for up to five years. We use the data set that covers 2018 to 2021.

We limit our analysis to individuals aged 21 to 70 who were employed in 2019, and we categorized them into two groups based on their prepandemic industry: those working in *essential* industries in 2019, which were exempt from pandemic mobility restrictions and lockdowns, and those working in *paralyzed* industries, which were subjected to them. The classification was provided by the Ministry of Labor and Promotion of Employment (MLPE) for 417 industries at the ISIC four-digit level and was based on Supreme Decree No. 044-2020-PCM of April 21, 2020, which laid out the lockdown policy. This approach has been widely used to estimate the labor-market impact of pandemic-related restrictions, not only in Peru (MLPE, 2020, 2021b,a) but in other countries (for example, Casarico and Lattanzio, 2022; Meekes et al., 2020).

Next, we classified the 139 detailed occupations reported in the survey according to their risk of automation by building a routinization-task-content index (RTI) closely following the methodology of Gasparini et al. (2021). Specifically, we used data from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) for descriptions of the tasks performed by Peruvian workers. Based on that, a routine-task-intensive job is defined as one that did not involve any of the following duties at least once a week: (i) managing or supervising others, (ii) planning others' activities, (iii) confronting problems, or (iv) writing articles or reports.

Next, we calculated an RTI, which is our proxy for automation risk, defined as the share of routine-task-intensive workers within each occupation at the two-digit ISCO level. Then, we linked the RTI estimate to each occupation in Peru's ENAHO panel and divided workers into two groups based on their RTI level prior to the pandemic: those with automation probability in the top quartile were classified as at high automation risk, and the rest of the jobs were considered as at low automation risk.[2]

We also considered using the pioneering and widely cited Frey and Osborne (2017) classification of automation risk. However, this measure has important limitations: (i) it does not account for task heterogeneity within occupations, and (ii) its estimations are based on US-specific occupational descriptions. The literature that studies the link between technology and labor markets finds that technology does not necessarily replace entire occupations or skills. Rather, it replaces certain routine tasks within occupations, allowing workers to specialize in nonroutine tasks (Acemoglu and Autor, 2011). Moreover, as shown by Autor and Handel (2013), tasks usually vary significantly within occupations. In view of this, we believe the RTI more accurately captures the potential automatability of the tasks performed by Peruvian workers. Nevertheless, we use Frey and Osborne (2017) estimates for a robustness check.

[2]Because individuals in the same occupation were assigned identical RTI levels, it was not possible to divide the sample into four equally sized quartiles. Consequently, the cutoff for the upper quartile was determined as the number that would include as close to 25% of the sample as possible.

After consolidating data from all sources, we obtained a comprehensive database of 4,881 workers who were observed working in 2019 and could be tracked from 2018 to 2021. Table 1 presents the distribution of the sample across paralyzed or essential industries and across occupations at high or low automation risk, along with the average hourly wage for each group and the composition of each group by gender, firm size, formalization, skill level, and sector. Out of the total, 2,286 (46%) workers were employed in paralyzed industries and 1,890 (38%) were at high automation risk.

Table 1: Descriptive statistics: Distribution of Workers by paralyzation and automation risk

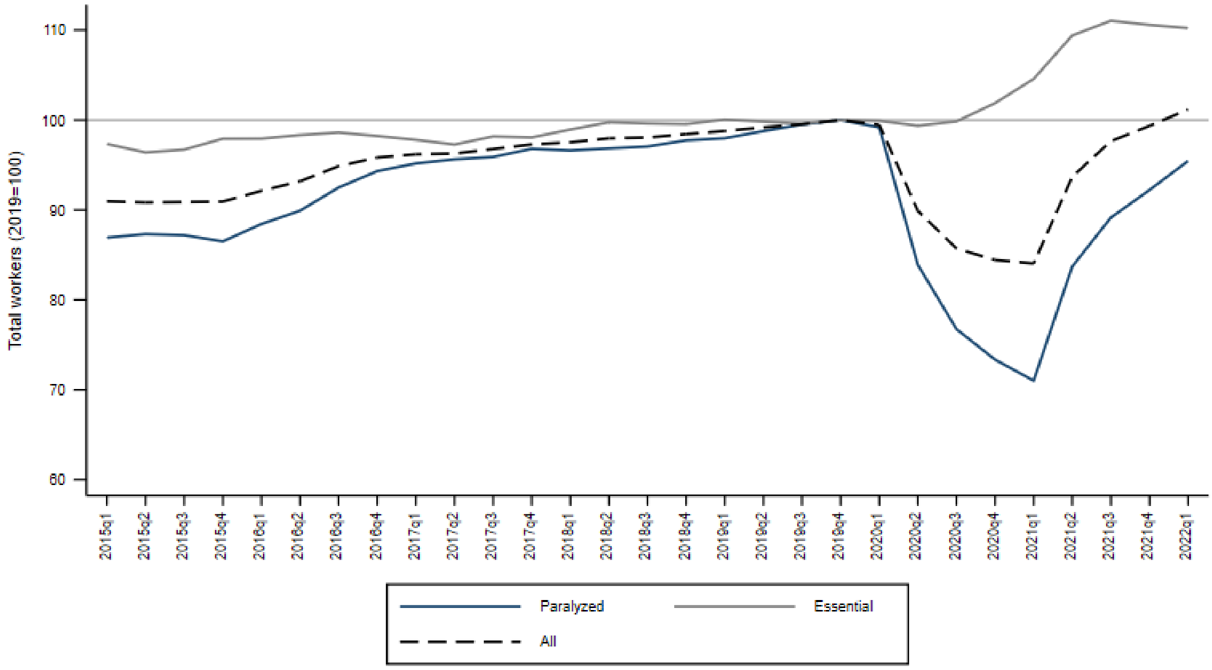
	Total workers	Paralyzed	Essential	High Automation Risk	Low Automation Risk	Paralyzed and High Automation Risk
Observations	4,881	2,286	2,595	1,890	2,991	392
Average hourly wage ($ PEN)	1322	1678	997	773	1740	964
Women	0.49	0.48	0.50	0.41	0.51	0.60
Men	0.51	0.52	0.50	0.59	0.49	0.40
Small and medium-sized firms	0.76	0.68	0.83	0.95	0.74	0.88
Large firms	0.24	0.32	0.17	0.05	0.26	0.12
Formal	0.25	0.36	0.14	0.05	0.44	0.15
Informal	0.75	0.64	0.86	0.95	0.56	0.85
Low-skilled	0.81	0.72	0.90	0.96	0.65	0.91
Medium-skilled	0.09	0.13	0.05	0.03	0.15	0.08
High-skilled	0.10	0.15	0.05	0.01	0.19	0.02
Agriculture and mining	0.40	0.03	0.73	0.73	0.08	0.11
Manufacturing and construction	0.13	0.22	0.05	0.08	0.18	0.23
Retail, restaurants and hotels	0.23	0.33	0.15	0.11	0.35	0.37
Services	0.17	0.31	0.06	0.06	0.29	0.24
Information, transport, finance and others	0.06	0.11	0.02	0.02	0.10	0.05

Note: This table presents descriptive statistics for the sample of individuals who were observed working in 2019 in the ENAHO panel aged 21 to 70 years old. The first column shows the total number of workers, along with the proportion of workers by gender, firm size, formality status, skill level, and sector. The second and third columns disaggregate this information for workers in essential and paralyzed industries, respectively. The fourth and fifth columns provide a similar breakdown for high- and low-risk occupations. Finally, the sixth column displays the distribution for workers in both paralyzed and high-risk jobs.

Paralyzed workers showed higher formalization rates, higher skill levels, received higher wages and were more heavily concentrated in manufacturing, retail, and services. Meanwhile, high-risk workers were predominantly informal, less skilled, lower paid, and concentrated in agriculture and mining. The intersection of the two groups constitutes 8% of the sample, with a greater concentration of women and low- and medium-skilled workers and with a more significant presence in the manufacturing, retail, and services sectors.

Using the cross-sectional ENAHO data (which allows us to include more years of observation), Figure 1 shows the evolution of jobs in paralyzed and essential industries in Peru between 2015 and 2022. Although both groups grew at a similar rate from 2017 to 2019, paralyzed jobs experienced a sharp decline after the COVID-19 outbreak, whereas essential jobs barely declined in 2020Q2 and continued growing thereafter. In this sense, essential jobs appear to be a suitable control group for measuring the labor-market impacts of COVID-19-related restrictions.

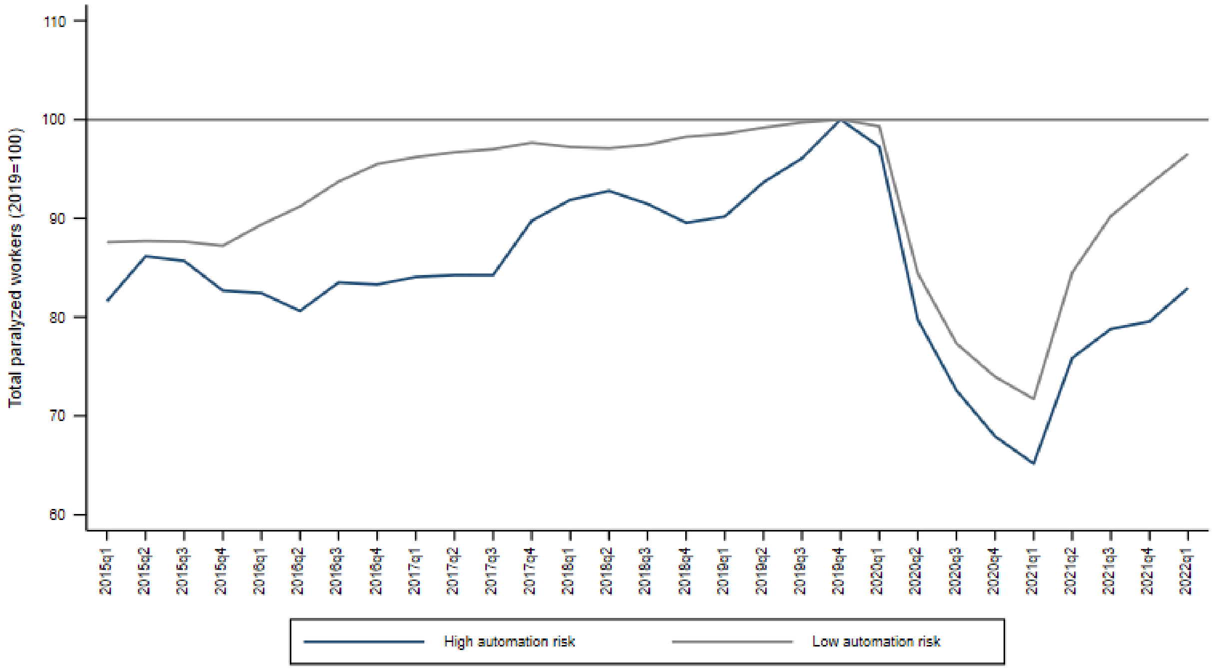
Figure 1: Evolution of paralyzed and essential jobs in Peru, 2015–22



Note: This figure displays the evolution of aggregate employment in Peru for industries that were ex post categorized as either essential or paralyzed because of pandemic-related restrictions. Data were obtained from the ENAHO cross-section database, which enables the addition of additional years at the aggregate level.

The number of paralyzed jobs at higher risk of automation fell substantially more than other paralyzed jobs, as shown in Figure 2. The quantitative exercises in the following sections seek to evaluate whether this occurred because of job automation.

Figure 2: Evolution of paralyzed jobs in Peru by automation risk, 2015–22



Note: This figure displays the evolution of paralyzed jobs in Peru, categorized by automation risk. High-risk jobs include those in the top quartile of the routinization-task-content index. Data were obtained from the ENAHO cross-section database, which enables the addition of additional years at the aggregate level.

3 Empirical strategy

Our identification strategy exploits the timing of the pandemic and the prepandemic allocation of workers in essential or non-essential industries and in occupations at high or low automation risk to estimate the impact of mobility restrictions on both the probability of being employed and the hourly wage. To achieve this, we define three econometric models using both difference-in-differences and triple-difference specifications, outlined below.

$$y_{ikt} = \alpha_i + \phi_k + \lambda_t + \delta_1(covid_t \times paralyzed_k) + \varepsilon_{ikt} \quad (1)$$

$$y_{ikt} = \alpha_i + \phi_k + \lambda_t + \delta_2(covid_t \times highrisk_i) + \varepsilon_{ikt} \quad (2)$$

$$
\begin{aligned}
y_{ikt} = {} & \alpha_i + \phi_k + \lambda_t + \delta_1(covid_t \times paralyzed_k) + \delta_2(covid_t \times highrisk_i) \\
& + \delta_3(paralyzed_k \times highrisk_i) + \delta_4(covid_t \times paralyzed_k \times highrisk_i) \\
& + \varepsilon_{ikt}
\end{aligned}
\tag{3}
$$

y_{ikt} is the variable of interest (employment-status dummy or hourly wage) for individual i in quarter t in industry k in 2019. δ_1 and δ_2 represent the double-difference coefficients and capture the differential change in the outcome after the onset of the pandemic between (i) workers in paralyzed industries versus workers in essential industries, and (ii) workers in high-risk occupations versus workers in low-risk occupations, respectively. δ_3 captures the differential change in the outcome of interest for workers in both paralyzed industries and high-risk occupations compared to workers in neither or only one of these categories. Meanwhile, δ_4 is the triple-difference coefficient, which captures the differential effect after the COVID-19 outbreak on the outcomes for workers both in paralyzed industries and high-risk occupations.

Finally, α_i, ϕ_k, and λ_t denote individual, industry, and time fixed effects. Individual fixed effects enable us to control for any individual-specific factors that may affect the likelihood of exposure to mobility restrictions and automation. Industry and time fixed effects allow us to control for any industry-specific or quarter-specific shock besides automation that could affect employment.

The first model measures the change in highly automatable jobs and their wages, regardless of whether those jobs were restricted during the pandemic. The second model estimates the impact of lockdowns and other COVID-19-related restrictions on occupation and wages, which provides a baseline measure of the pandemic's effect on overall employment and wages. Finally, the third model captures the impact of the pandemic on highly automatable jobs that were affected by mobility restrictions. This is the model of greatest interest to us, as it allows us to determine whether pandemic-related restrictions encouraged labor automation.

The main identification assumption in these models is that, in the absence of COVID-19, the probability of being employed for treated workers would have evolved with a similar trend to control workers. To test the validity of this parallel-trends assumption in our triple-differences model, we estimate the following dynamic triple-differences equation:

$$\begin{aligned} y_{ikt} = \alpha_i + \phi_k + \lambda_t + \sum_{j \in T} \delta_{1j}(\gamma_t \times paralyzed_k) + \sum_{j \in T} \delta_{2j}(\gamma_t \times highrisk_i) \\ + \sum_{j \in T} \delta_{3j}(paralyzed_k \times highrisk_i) + \sum_{j \in T} \delta_{4j}(\gamma_t \times paralyzed_k \times highrisk_i) \\ + \varepsilon_{ikt} \end{aligned} \tag{4}$$

Here, γ_t are dummies for every j quarter in T (2018Q1–2021Q4, excluding 2019Q4). If $\delta_4 j$ is nonsignificant for prepandemic quarters, the parallel-trends assumption cannot be rejected, and therefore our empirical strategy is reliable.

4 Results

4.1 Main Results

Table 2 summarizes the results from estimating equations 1, 2, and 3 for employment status (Models 1–3) and hourly wages in logarithms (Models 4–6). Each difference helps us to gradually disentangle the impact of mobility restrictions on highly automatable workers. First, Models 1 and 4 show that workers in high-risk jobs in general (whether paralyzed or not) did not experience a significant decrease in employment rates relative to low-risk jobs, while their wages increased slightly more. This probably reflects the higher share of high-risk jobs in essential industries (79% in 2019) than in paralyzed industries (21%).

Second, Model 2's estimates indicate that COVID-19-related restrictions resulted in an overall contraction of 9 percentage points across all job types, while Model 5 shows a similar trend for wages, with a decrease of approximately 61.3%. These estimates provide a baseline measure of the pandemic-related paralyzation effect that was common to all types of workers.

Finally, Model 3 shows that mobility restrictions had a disproportionate impact on highly automatable jobs, resulting in a contraction that was 18.4 percentage points higher than for other jobs. This represents a contraction of 22.5%, based on a reference employment rate of 85.4%. Similarly, the triple-difference coefficient from Model 6 was -1.36, indicating that hourly wages decreased 74.1% more for highly automatable jobs in industries affected by mobility restrictions than for other jobs.

Table 2: Effect of mobility restrictions and automation risk on the labor market

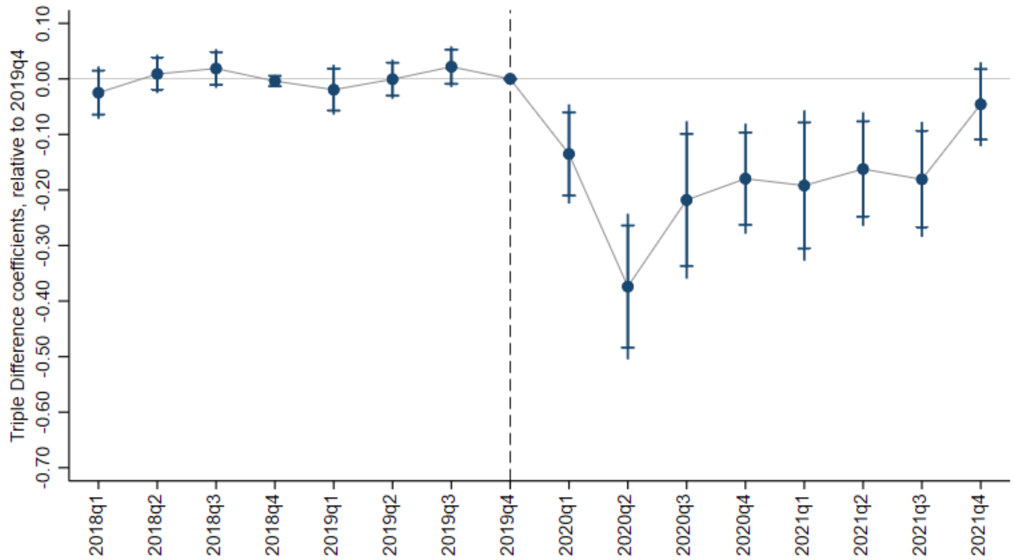
	Employment			Wages (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × High Aut Risk	0.0373		0.0537***	0.633**		0.678***
	(0.0342)		(0.0199)	(0.319)		(0.192)
Post × Paralyzed		-0.0901***	-0.0290		-0.958***	-0.352**
		(0.0246)	(0.0235)		(0.234)	(0.174)
Post × High Aut Risk × Paralyzed			-0.184***			-1.358***
			(0.0249)			(0.238)
Observations	19431	19431	19431	19431	19431	19431
Adjusted R^2	0.156	0.163	0.170	0.194	0.198	0.204

Note: This table displays the estimation of Equations 1, 2, and 3 for the employment-status dummy (columns 1–3) and the logarithm of wages (columns 4–6) using data from 2018 and 2021. High automation risk is defined as workers in the routinization-task-content index's fourth quartile. All regressions include individual, industry, and quarter fixed effects. Clustered robust standard errors at the industry-individual level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

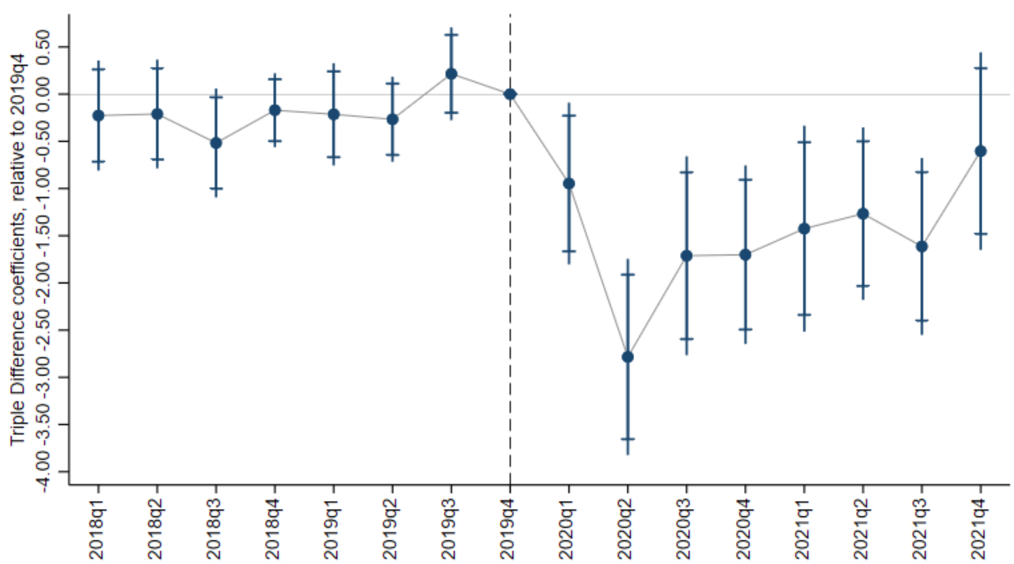
By isolating the paralyzation effect that was common to both high-risk and low-risk jobs, Models 3 and 6 provide insight into whether the pandemic accelerated job automation in the Peruvian labor market. These results are valid if *treated* jobs (that is, workers paralyzed by restrictions and at high risk of being automated) would have evolved in a similar fashion to other jobs if the pandemic had not occurred. The validity of this assumption is tested by estimating Equation 4. As shown in Figure 3 (Panels A and B), computed quarterly, point estimates for pretreatment quarters are not significant, both at 90% and 95% confidence levels, thus not providing evidence to reject the parallel-trends assumption.

Figure 3: Effect of mobility restrictions and automation risk on the labor market: Dynamic triple-difference model, 2018–21

A. Employment



B. Wages



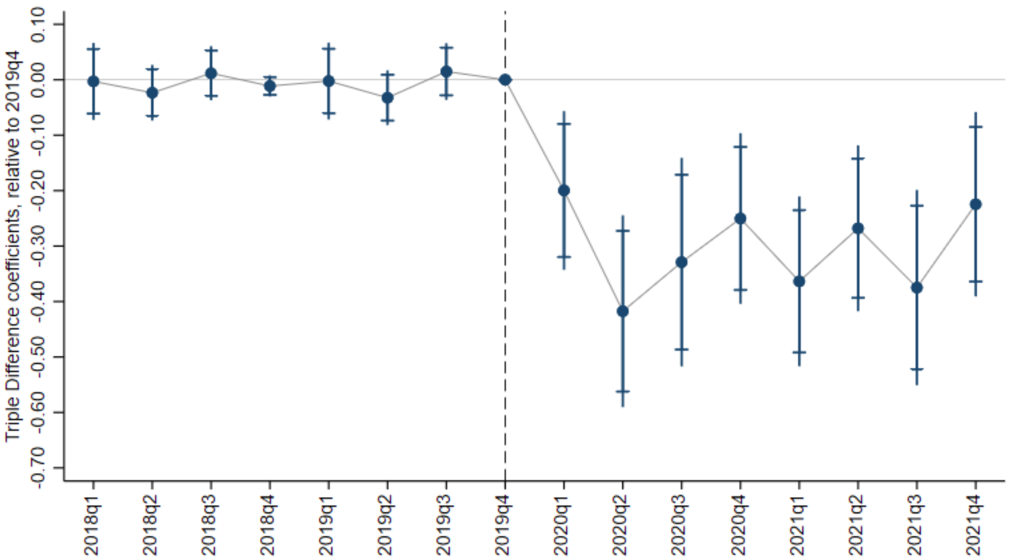
Note: The figure shows quarterly point estimates, along with the 90% and 95% confidence intervals of the dynamic triple-difference equation described in Equation 4 for the employment-status dummy (Panel A) and the logarithm of wages (Panel B) using data from 2018 to 2021. High automation risk is defined as workers in the routinization-task-content index's fourth quartile. Standard errors are clustered at both the individual and industry levels.

Quarterly estimates allow us to observe that workers at high risk of automation had lower employment rates and hourly wages up to 18 months after the pandemic outbreak. Afterward, these workers' employment rates and wages recovered to levels similar to the control group's.

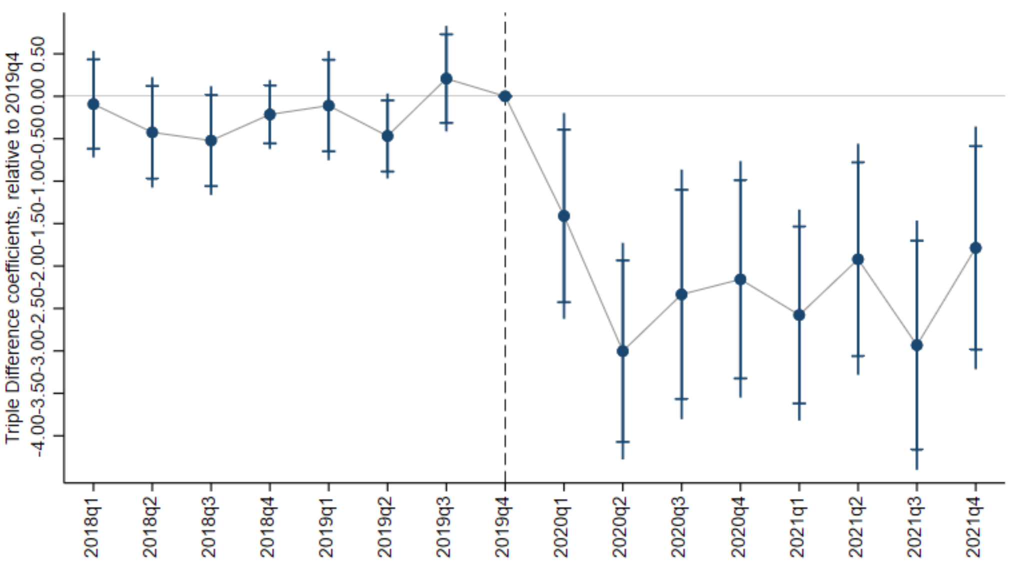
Various factors may have influenced this recovery. For instance, displaced workers may have moved to low-risk occupations. As argued by Christenko (2022), occupational mobility could be a way in which workers adapt to automation. To check whether this hypothesis is true, we run Models 3 and 6 including only workers who did not move from high-risk to low-risk occupations after the outbreak. As shown in Figure 4, job contraction for high-risk workers is stronger and more prolonged when occupational mobility is not accounted for. This evidence suggests that employment recovery was driven by occupational mobility.

Figure 4: Effect of mobility restrictions and automation risk on the labor market (ignoring occupational mobility from high- to low-risk occupations): Dynamic triple-difference model, 2018–21

A. Employment



B. Wages



Note: The figure shows quarterly point estimates, along with the 90% and 95% confidence intervals of the dynamic triple-difference equation described in Equation 4 for the employment-status dummy (Panel A) and the logarithm of wages (Panel B) using data from 2018 to 2021 and not including workers that moved from high- to low-risk jobs after 2020. High automation risk is defined as workers in the routinization-task-content index's fourth quartile. Standard errors are clustered at both the individual and industry levels.

4.2 Robustness

We explore the robustness of our main results by changing the specification of the triple-difference model and the definition and threshold of highly automatable occupations. The results are shown in Table 3.

First, we estimate the model including interacted year-industry fixed effects. The objective of this exercise is to control for year-specific shocks (other than automation) that may have occurred in certain industries and that could have affected employment levels. Though many degrees of freedom are lost under this specification because we include 449 additional coefficients, it is important to verify that our results are not driven by such shocks. Results show that the significance of our triple-difference coefficient is robust to the inclusion of year-industry fixed effects, and its absolute magnitude is slightly lower (-11 percentage points compared to -18.4 for employment rate, and -0.6 percentage points compared to -1.36 for hourly wages).

Second, we change the threshold for classifying an occupation as highly automatable, now including also workers in the third automation-risk quartile. Unsurprisingly, the absolute magnitude of the triple-difference coefficient is lower than in the main scenario but its statistical significance remains. In a third exercise, we build an alternative RTI, following Gasparini et al. (2021). In addition to the existing criteria, we classified jobs as routine-intensive if they did not involve (i) calculating budgets or costs or (ii) giving presentations. The coefficients using this definition are lower than in the main scenario, but their sign and significance remain.

Finally, we use an alternative measure of automation risk, using Frey and Osborne (2017) estimates. Again, the coefficients are lower, but they continue to be statistically significant for wages.

Table 3: Triple-difference model: Alternative specifications

	Baseline	Interacted fixed effects	3rd and 4th RTI Quartiles	Alternative RTI	FO Estimates
			A. Employment		
Post × High Aut Risk	-0.184***	-0.110**	-0.0949**	-0.0840**	-0.0474
× Paralyzed	(0.0249)	(0.0439)	(0.0378)	(0.0378)	(0.0483)
Adjusted R2	0.219	0.246	0.216	0.214	0.216
			B. Wages		
Post × High Aut Risk	-1.358***	-0.604*	-0.881***	-0.913***	-1.037***
× Paralyzed	(0.238)	(0.310)	(0.325)	(0.289)	(0.265)
Adjusted R2	0.251	0.266	0.250	0.250	0.310
N	19431	19156	19431	19431	19431
Individual FE	X	X	X	X	X
Quarter FE	X	-	X	X	X
Industry FE	X	-	X	X	X
Quarter × Industry FE	-	X	-	-	-

Note: This table displays the triple-difference coefficients resulting from estimating Equation 3 for the employment-status dummy (Panel A) and the logarithm of wages (Panel B) under different specifications. The first column is the baseline scenario (similar to Table 2). The second column includes interacted year-industry fixed effects. The third column includes the routinization-task-content index's (RTI's) third quartile in the group of high-risk jobs. The fourth column uses a definition of RTI with two additional conditions (not calculating budgets or costs, and not giving presentations). The last column uses Frey and Osborne (2017) (FO) estimates of automation risk instead of RTI estimates. Clustered robust standard errors at the industry-individual level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

4.3 Heterogeneous Effects

This subsection analyzes the results of the main specification for different subsamples. We estimate the triple-difference models for employment and wages by gender, firm size, formality, skill level, and sector. We suspect that women, small and medium-sized firms, less-skilled workers, informal workers, and those in the retail, manufacturing, and services sectors may have been differentially affected by mobility restrictions because of their heightened exposure to paralyzed industries or high-risk jobs. The findings of this analysis are illustrated in Figure 5.

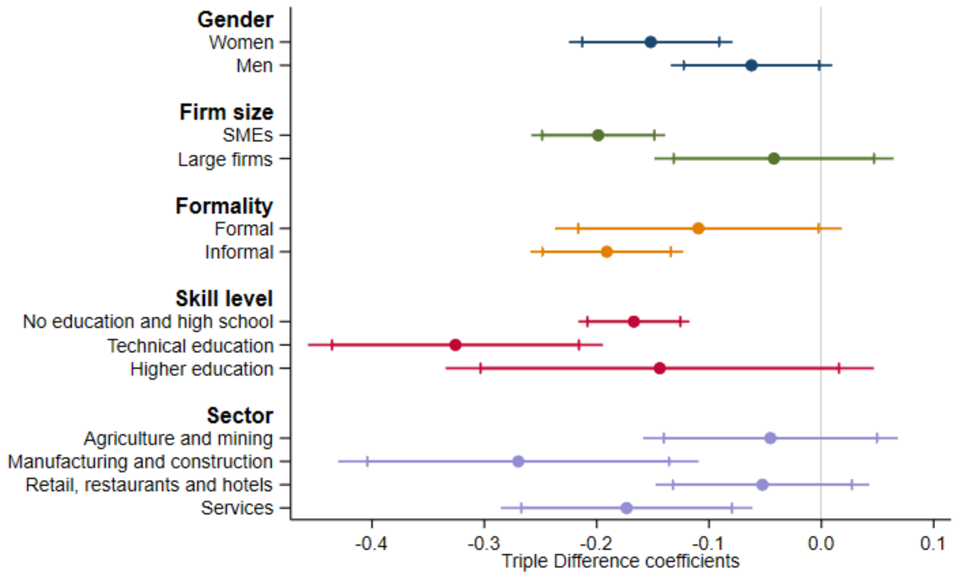
Results suggest that automation effects on employment and wages are primarily concentrated among workers in manufacturing, construction, and services. Notably, the effect is most pronounced among medium-skilled individuals (defined as those who possess technical education), followed by those who are less skilled (with no education or only high school education). The effect is nonsignificant for high-skilled workers (those with higher education). These findings align with the existing literature on automation in developed countries, which has confirmed the hypothesis that medium-skilled workers are most vulnerable to displacement by automation. The validity of this hypothesis was not as clear for developing countries, underscoring the significance of this study's findings for pandemic-related restrictions in Peru.[3]

In addition, the effects are especially significant for informal workers and for small and medium-sized firms, defined as businesses employing fewer than 100 workers. Probably, informal and small firms operating in the services and manufacturing sectors—which are typically less efficient and have limited resources to invest in technology—were incentivized during the pandemic to adopt technology. Furthermore, results suggest that women are more affected than men, which probably reflects women's greater level of informality than men and their greater concentration in the services sector.

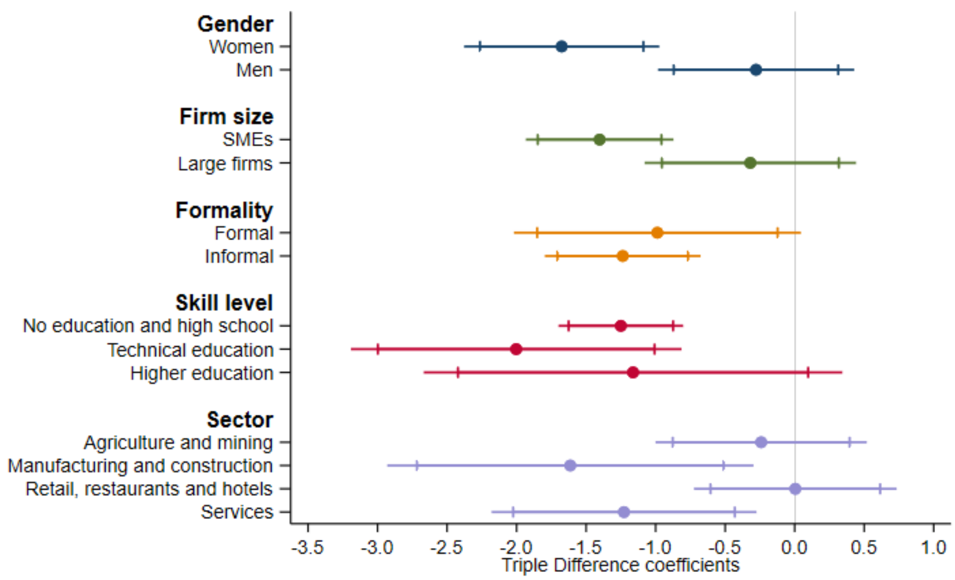
[3]While technology adoption and automation have contributed to labor polarization in developed countries because routine-intensive tasks are concentrated among medium-skilled workers (Autor et al., 2003; Goos and Manning, 2007), some evidence suggests that the same does not hold true in developing countries. For instance, studies of various regions, including eastern Europe, Africa, Latin America, and Asia, have not found evidence of labor polarization in developing countries (Gasparini et al., 2021; Brambilla et al., 2022; Maloney and Molina, 2016; Lewandowski, 2017).

Figure 5: Heterogeneous effects of mobility restrictions and automation risk on the labor market: Triple-difference model

A. Employment



B. Wages



Note: This figure presents the triple-difference coefficient estimated from Equation 3, along with the 90% and 95% confidence intervals for the employment-status dummy (Panel A) and the logarithm of wages (Panel B), using data from 2018 to 2021 for various subsamples by gender, firm size, formality status, skill level, and sector. High automation risk is defined as workers in the routinization-task-content index's fourth quartile. Standard errors are clustered at both the individual and industry levels.

5 Conclusion

This paper explored how mobility restrictions can incentivize automation in emerging economies using Peru as a case study. We used a large rotating household panel and identified jobs more vulnerable to being replaced by technology adoption. Automation risk was defined using Peruvian workers' task descriptions collected by the OECD-PIAAC.

We exploited variation in Peru's lockdown policy during the COVID-19 pandemic, which allowed certain essential economic activities to continue, and within-industry variation of high- versus low-automation-risk jobs, a classification based on a routine-task-intensity index.

The results show that mobility restrictions caused a higher employment and wage drop in jobs at higher risk of being automated. We show that paralyzed high-risk workers recovered employment rates similar to other workers 18 months after the COVID-19 outbreak, a result driven by workers who moved from high-risk to low-risk occupations. This study also found significant heterogeneous effects, as impacts are concentrated among workers in manufacturing, construction, and services; medium-skilled and low-skilled individuals; women; informal workers; and small and medium-sized firms.

These findings suggest that pandemic-related mobility restrictions may have helped alleviate technology-adoption constraints faced by tightly constrained firms, such as smaller, informal, and service-based ones. As a result, these firms likely focused on adopting basic technologies, rather than more sophisticated ones such as robots and artificial intelligence. For example, the adoption of security cameras to reduce in-person interactions in various businesses, such as grocery stores and hair salons, may have reduced the demand for door attendants and other security-related jobs. Naturally, validating this conclusion would require additional data on direct technological adoption, which are often challenging to collect in emerging economies.

Although this analysis offers only a short-term perspective for a single developing economy, which must be complemented with analyses for other countries, it provides key evidence on how mobility restrictions can accelerate automation and increase the vulnerability of routine-intensive workers in developing economies. Moreover, it shows that occupational mobility is a potential channel through which workers adapt to automation. This conclusion has key policy implications. As highlighted by other studies (for example, Nedelkoska and Quintini, 2018) it reinforces the need to design training policies to equip workers with cognitive and nonroutine skills that help them transition to career paths less affected by technology adoption.

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