Mobility Restrictions and Automation in the Developing World: Evidence from Peru's Labor Market*

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Abstract

Mobility restrictions have the potential to accelerate automation by increasing constraints on the use of labor. Using a triple-difference empirical strategy, this paper estimates the impact of pandemic-related restrictions on labor market outcomes in Peru, focusing on differences across occupations with varying exposure to automation risk. Our results indicate that mobility restrictions significantly decreased employment rates (-13.5%) and hourly labor earnings (-64%) 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, and informal workers, and were present across the skill distribution, with the largest effects among medium-skilled workers. Evidence suggests that occupational mobility from high-risk to low-risk jobs drove recovery afterwards. These patterns are consistent with firms adjusting to disruptions in labor availability by reducing reliance on routine-intensive tasks and highlight how labor supply shocks can interact with automation risk in developing economies.

Keywords: automation, mobility restrictions, labor markets, occupational mobility, jobs
JEL Codes: J21, J46, J62, O33.

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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.

This paper investigates whether exogenous shocks that limit labor mobility could alleviate these barriers to automation and affect labor outcomes differently across occupations with varying exposure to automation risk in the developing world. Specifically, we focus on the repercussions of COVID-19-related mobility restrictions in Peru, which imposed unprecedented constraints on firms, workers' mobility, and in-person interactions. Such restrictions could have displaced routine, in-person work through several channels: an employer facing a binding constraint on labor use could reorganize production around fewer routine tasks, or workers with no employer at all could be displaced as consumers and firms substituted digital payment and delivery technologies for in-person exchange.

The outbreak of the COVID-19 pandemic caused severe disruptions in emerging labor markets. According to high-frequency harmonized surveys (Khamis *et al.*, 2021), around 34% of developing economies' labor force stopped working in the early stage of the pandemic, a situation that was particularly severe in Latin America and the Caribbean (48%), the most affected region, with critical cases like Peru (59%).

The magnitude of the shock suffered by Latin America and the Caribbean (LAC) is explained by several factors. First, LAC Gross domestic product (GDP) contraction was the largest when compared to other regions, falling 7% in 2020. Second, the majority of LAC workers were (and continue to be) informal (57% of the total workforce), highly

concentrated in in-person services activities, more susceptible to contagion, and usually not covered by government policies aimed at protecting formal jobs (Acevedo *et al.*, 2021). Peru was particularly affected, since GDP contraction during the pandemic was higher (11%) and informality, already at 72.7% before the pandemic, rose to 76.8% in 2020, which makes it an interesting case for studying emerging labor market dynamics.

Besides these short-term effects, COVID-19 could also have profound long-lasting implications for labor markets, due to its potential to stimulate adjustments consistent with automation-related substitution. In particular, the need to limit in-person interactions to reduce contagion could have incentivized firms to reduce reliance on tasks that are more easily automated, as these tasks may be more easily reorganized, digitized, or substituted when in-person work is constrained.

In fact, according to a World Economic Forum (2020) survey, around 50% of business leaders were set to accelerate the automation of jobs in their companies after the pandemic broke out, and 43% of businesses indicated that they were set to reduce their workforce because of technology integration. Additionally, there is already evidence that documents a strong increase in digital adoption and online transactions as a result of the COVID-19 pandemic (Cerda *et al.*, 2023).

To estimate whether mobility restrictions had stronger effects on workers in occupations more exposed to automation risk, we leverage a rich longitudinal household survey in Peru that allowed us to follow workers from 2018 to 2021. We divided workers into two categories based on their industries before the pandemic: those in paralyzed industries, affected by lockdowns and other mobility restrictions; and those in essential industries, exempt from such constraints. Furthermore, jobs were categorized based on their tasks: occupations predominantly involving routine tasks were classified as highly automatable, whereas those with fewer routine tasks were classified as less automatable.

Using a triple-difference empirical design, we exploited the unexpected timing of the pandemic and the pre-existing industry and occupation of workers to estimate the im-

pact of mobility restrictions on labor market outcomes across occupations with different automation risk. This approach enabled us to isolate differential effects associated with automation exposure from the broader economic impact of the pandemic by comparing post-pandemic changes between high and low automation risk occupations across industries differentially exposed to mobility restrictions.

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 labor earnings 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, and workers in small and medium-sized enterprises, and that they are present across the skill distribution, with the largest effects among medium-skilled workers.

These results are robust to a range of alternative specifications and measures of automation risk. Furthermore, we find that our results do not appear to be driven by a shift towards teleworking.

This research contributes to different segments of the literature on automation. First, it presents new evidence that underscores how labor supply disruptions interact with automation risk in developing economies. Previous studies on this matter have found mixed results, some finding null or modest links between technology adoption and employment and wages (De Vries *et al.*, 2020; Novella *et al.*, 2023), while others find a strong negative association (Shapiro and Mandelman, 2021) and a decline of jobs that are more vulnerable to automation (Gasparini *et al.*, 2021; Brambilla *et al.*, 2022).[1]

Second, it contributes to the literature on the links between occupational mobility and automation. Prior research has shown a heightened level of occupational mobility dur-

[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)

ing eras of significant economic transformations (for example, Parrado *et al.*, 2007). And although the susceptibility to technological change is generally shared among occupations with analogous tasks, some occupations align more closely with others less affected by automation, thus providing a way in which workers can adapt to job replacement (Christenko, 2022). Our findings provide suggestive evidence in that regard, as workers in highly automatable jobs who transitioned to occupations with lower automation risk after the shock were more likely to be employed compared to those who remained in their original jobs.

Third, our research contributes to the literature exploring the implications of COVID-19 on automation—a subject that remains underexplored for both developed and developing countries. For the US, Ding and Molina (2020) and Chernoff and Warman (2022) suggest that workers at higher risk of automation were more vulnerable to the COVID-19 shock. For Chile, Egana-delSol *et al.* (2022b) 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.* (2023) find that the pandemic reduced job openings and employment in highly automatable occupations in Colombia, using occupation-city-level data.

In addition to these contributions, our empirical approach offers two advantages relative to previous studies. First, we rely on individual-level data, which allows us to track the same workers over time and determine not only whether they lose their jobs, but also how they adjust—whether by transitioning to a different occupation or remaining unemployed. In contrast, industry- or occupation-level data capture aggregate changes in job volume but cannot distinguish between job losses and occupational transitions, nor can they identify which workers are affected or how they respond. This distinction is crucial: a decline in job volume might reflect a mix of job losses and job shifts, but understanding the individual-level experience provides a more granular picture of employment outcomes and adaptation mechanisms.

Second, our triple-difference empirical strategy helps isolate the effects of automation exposure more effectively by comparing post-pandemic changes between workers in high and low automation risk occupations across industries differentially exposed to mobility restrictions. This approach allows us to distinguish the interaction between mobility restrictions and automation risk from the broader effects of the pandemic on paralyzed industries and on high-risk occupations.

This paper is organized as follows. Section 2 provides institutional background on Peru's economic structure, technology adoption, and the COVID-19 mobility restrictions. Section 3 details the data and the construction of variables used in the analysis. Section 4 presents our empirical strategy for estimating how pandemic-related mobility restrictions affected labor outcomes across occupations with different exposure to automation risk in Peru. Section 5 presents the main results, robustness checks, and heterogeneous effects. Finally, Section 6 discusses policy implications and concludes.

2 Automation and informality in Peru

Whether mobility restrictions displaced workers in occupations exposed to automation depends on three features of the Peruvian economy: how production is organized outside the registered corporate sector, how asymmetrically the pandemic fell across activities, and what technology was available to substitute for the work that stopped. This section takes these in turn and closes by setting out the channels through which displacement could operate.

2.1 Peru's dual labor market in the eve of the pandemic

Peru's economy in 2019 combined the features of a middle-income Latin American economy with an unusually large share of production outside the registered sector. Gross value added was spread fairly evenly across broad sectors, ranging from 15 percent in

retail, restaurants and hotels to 23 percent in manufacturing and construction. Employment was not. Agriculture and mining together with retail, restaurants and hotels absorbed more than half the workforce, while transport, information, finance and real estate produced a fifth of value added with under a tenth of employment (Table 1). Within agriculture and mining the divergence is sharper still, since agriculture accounts for almost all of the group's employment and mining for most of its output. These gaps between a sector's share of output and its share of work are the defining feature of Peru's dual economy (World Bank, 2017; OECD, 2025).

Informality runs through the same divide. In 2019, 72.7 percent of employed workers held informal jobs, a figure our own measures reproduce on the same universe, but the rate varied sharply across activities, from 94 percent in agriculture and mining to 46 percent in services, with retail, restaurants and hotels at 76 percent and manufacturing and construction at 71 (Table 1). Informality of this magnitude is not a single phenomenon, and the distinction between its forms matters for what follows. Following the definitions of the International labor Organization, a job is informal when it carries no social security protection, and a production unit belongs to the informal sector when it is an unincorporated household enterprise that is neither registered nor keeps formal accounts. Crossing the two yields three categories that we use throughout: formal employment; informal employment in the informal sector, which is work in unregistered production units; and informal employment outside the informal sector, which is work without social security in units that are registered or institutional.

The distinction maps onto two margins along which firms operate outside the regulatory perimeter (Ulyssea, 2018). On the extensive margin a production unit never registers at all. On the intensive margin a registered firm hires part of its workforce without contracts. The two need not move together, so an aggregate informality rate is not a sufficient statistic for what happens to workers after a shock. Cisneros-Acevedo (2022) shows this for Peru's trade liberalization, where tariff reductions drove the least productive unreg-

istered firms out of business while inducing surviving registered firms to hire informally, so that measured informality rose even as the number of informal firms fell. A third arrangement sits outside both margins: employment by private households, which the international definitions place outside the informal sector because a household is not an informal sector production unit.

Table 1: Peruvian economic structure and informality by sector, 2019

Sector group	GDP share (%)	Employment share (%)	Informality rate (%)
Agriculture and mining	19.7	25.3	93.6
Manufacturing and construction	22.6	15.6	70.7
Retail, restaurants and hotels	15.0	26.5	76.1
Transport, information, finance and real estate	21.2	9.3	75.8
Services	21.5	23.3	46.4

Note: All figures refer to 2019. GDP shares are computed from INEI's national accounts at the 54-activity level and expressed as a percentage of gross value added at constant 2007 soles, which excludes taxes on products and import duties. Employment shares and informality rates are authors' calculations from the 2019 ENAHO annual cross-section, covering all employed workers of any age and weighted by the survey expansion factor; the informality rate is the share of employed workers holding informal jobs, using INEI's constructed indicator. Sector groups aggregate CIIU rev.4 sections: agriculture and mining (A and B); manufacturing, utilities and construction (C, D, E and F); retail, restaurants and hotels (G and I); transport, information, finance and real estate (H, J, K and L); and services (M through U). The agriculture and mining group combines two activities with opposite characteristics: agriculture accounts for almost all of the group's employment and mining for most of its value added. Sources: INEI National Accounts (Instituto Nacional de Estadistica e Informatica, 2024a); INEI ENAHO 2019; authors' calculations.

These arrangements differ in how a shutdown policy reaches them. Peru's restrictions were assigned to economic activities and were enforceable against registered establishments, which have an address, a payroll and an inspectable legal existence. An unregistered producer faced the same restrictions in practice, through checkpoints, sus-

pended transport and the absence of customers, but not as a matter of enforceable law. Since registered and unregistered producers coexist within the same activities rather than occupying separate ones (Ulyssea, 2020; de Beer *et al.*, 2016), the population a policy of this kind reaches is defined jointly by activity and by position on the formal to informal margin.

2.2 The pandemic shock and the reactivation plan

Peru suffered one of the deepest pandemic-era recessions in Latin America and the highest confirmed case-fatality rate in the world. Limited health system capacity and widespread informality blunted the effectiveness of government interventions (Villar *et al.*, 2024; Cáceres-Cabana *et al.*, 2021). Real GDP contracted by 10.9 percent in 2020, more than twice the contraction in Chile or Colombia. Aggregate recovery was swift, with output growing 13.4 percent in 2021, but the informality rate rose to 76.8 percent in 2020 and remained elevated through 2022, indicating that the labor market absorbed the shock through a shift toward more precarious arrangements (Deelen *et al.*, 2018; Lachowska *et al.*, 2020; Garita *et al.*, 2024).

The government response was early, stringent and centrally coordinated (Benítez *et al.*, 2020). On 15 March 2020 it declared a state of emergency, closed borders, and specified which activities were essential and therefore exempt from the restrictions, among them healthcare, food supply, financial services, telecommunications and sanitation. On May 2nd a multi-sectoral working group established four phases in which firms in selected activities, identified at the ISIC four-digit level, could resume operating in whole or in part, with the sequence determined primarily by workers' exposure to contagion risk (MTPE, 2021a). Mining, construction, services and commerce resumed in the first phase subject to health authorization, manufacturing and retail in the second, and tourism, entertainment and religious activities in the third and fourth. The schedule produced a classification of 417 four-digit activities by the severity of the restrictions each faced, which we use in

Section 3 to define the treatment. Alongside it, the government legislated in favour of remote work and launched two subsidized lending programmes that together reached roughly 240,000 firms, most of them micro and small enterprises, along with a sequence of emergency household transfers.

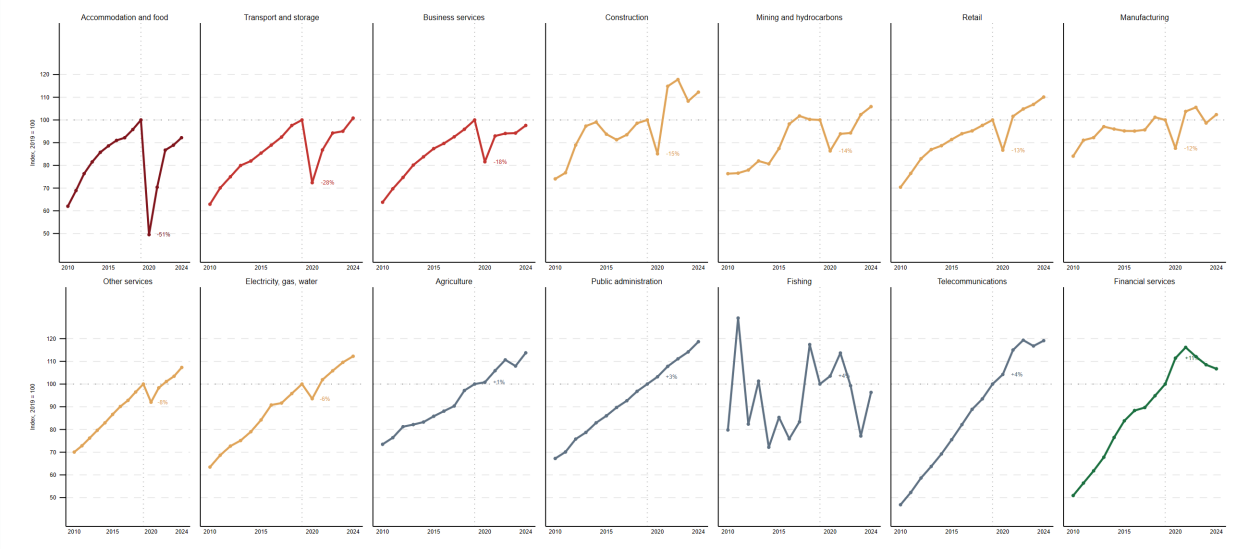
The restrictions bound, and the evidence is unambiguous. Peru's score on the Oxford stringency index averaged 92.47 between April and June 2020 (Hale *et al.*, 2021), and time spent at places of residence rose by 33.65 index points over the same period, one of the highest values in Latin America against a regional average of 24.15 (Cueva *et al.*, 2021). They did not bind equally, however. Across 242 subnational regions of nine Latin American and African countries, Peru among them, the reduction in work-related mobility during the first lockdown was smaller in high-poverty regions (Bargain and Aminjonov, 2021), and a nationally representative Peruvian survey fielded in May 2020 found that economically vulnerable respondents were more likely to oppose the quarantine and to leave home in order to work (Carreras *et al.*, 2021).

The aggregate contraction conceals substantial variation across activities. Figure 1 plots real output by sector indexed to 2019. Accommodation and food fell by more than half in 2020, transport and storage by 28 percent and business services by 18 percent, while agriculture grew slightly, financial services expanded and public administration was unaffected. Construction and retail fell sharply and recovered by 2022. The essential and paralyzed distinction is in effect a policy-assigned categorization of this variation: activities in which in-person interaction could be replaced by remote work or by deliveries of essential goods continued operating, while activities requiring physical proximity stopped.

One feature of this episode distinguishes it from the crises against which the informal sector's behaviour is usually assessed. Informal employment is ordinarily countercyclical, expanding in downturns as displaced workers move into own-account activity (Ulyssea *et al.*, 2025). That did not happen here. Across six Latin American countries

including Peru, informal employment contracted alongside formal employment in 2020, transitions from informal to formal work collapsed, and most informal workers who lost work left the labor force rather than moving into another informal activity (Maurizio *et al.*, 2023). The activities that normally absorb displaced workers, small-scale trade, street vending, food preparation and personal services, were themselves shut down.

Figure 1: Peru: sectoral real output indexed to 2019, 2010–2024



Note: Each panel shows annual real output for one INEI 14-activity sector, indexed so that 2019 = 100. The dotted vertical line marks the reference year (2019); the dotted horizontal line marks the 2019 level. The 2020 percent change relative to 2019 is annotated in each panel. Sectors are ordered from the largest to the smallest 2020 contraction. Source: INEI National Accounts, constant 2007 soles (Instituto Nacional de Estadistica e Informatica, 2024a).

2.3 Technology adoption in an economy of small and unregistered producers

A shock that constrains the use of labor can accelerate the substitution of technology for workers. In task-based models of production, firms allocate tasks between labor and capital according to relative factor costs, and a rise in the effective cost or unavailability of labor shifts the allocation toward capital (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018). Acemoglu and Restrepo (2022) formalize the point: a higher cost of labor

raises the adoption and development of automation technologies, a mechanism with a long history (Habakkuk, 1962). Recessions are when routine-intensive employment is shed and does not return (Jaimovich and Siu, 2020; Hershbein and Kahn, 2018).

Applied to Peru, this account requires a qualification, because it presupposes a firm that can finance the substitution and workers it employs. Credit constraints and low labor costs are precisely the configuration under which returns to labor-saving capital are lowest (Foster and Rosenzweig, 2010), and physical automation is not the margin on which developing economies appear to adjust: Maloney and Molina (2019) find that robots displace labor in advanced economies but are associated with increased demand for operators and assemblers in developing ones. More fundamentally, most Peruvian workers are not wage employees of a firm at all, and a substantial share work in units that are themselves unregistered.

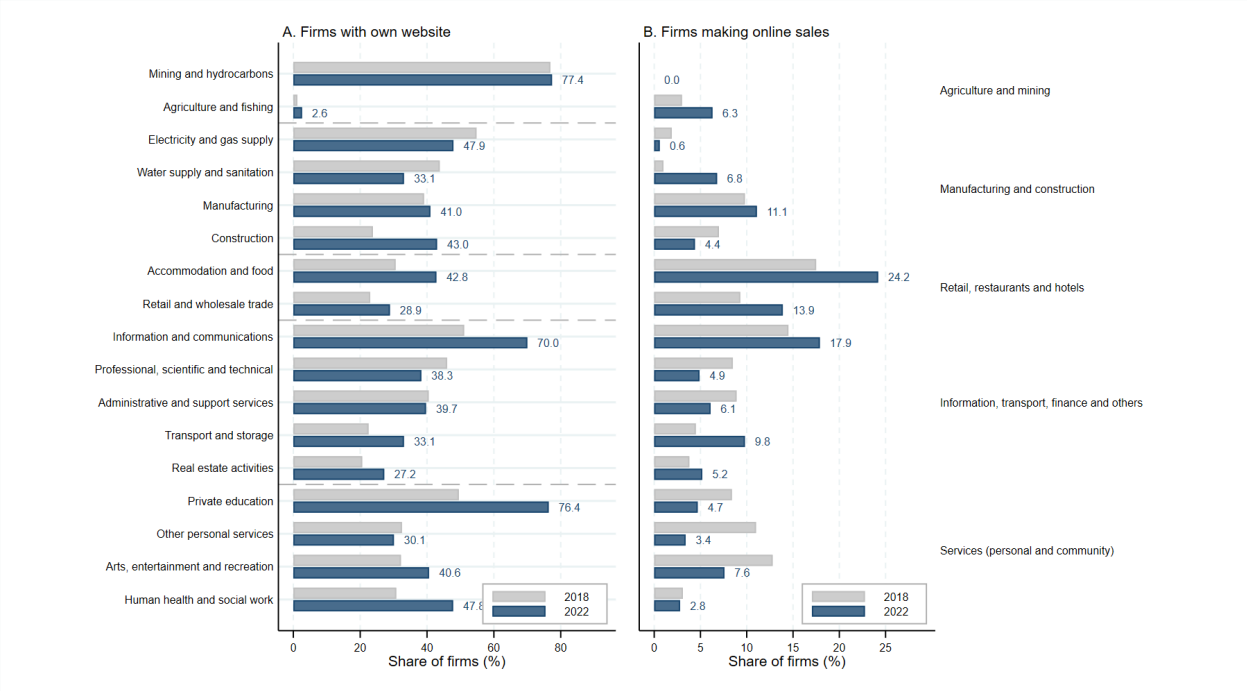
The task-based framework nevertheless applies, because what technology substitutes for is a task rather than an occupation (Acemoglu and Autor, 2011; Autor, 2013), and the party adopting a technology need not employ whoever previously performed the task. When households pay merchants through mobile wallets rather than cash, or order through delivery platforms rather than visiting a market, the intermediation task that a street vendor performs is displaced by technology the vendor never adopted.

Peru's pandemic experience shows that this is where technology moved. Digital payment adoption accelerated sharply during the restriction period. *Plin*, one of the country's two dominant mobile wallets, launched in May 2020 inside the first lockdown; by the end of 2023 it and *Yape* together accounted for more than half of all retail cashless transactions, having overtaken cards, with roughly seventeen and thirteen million users respectively (Andia *et al.*, 2026). Electronic commerce moved from a low base, with only 8.1 percent of small and medium enterprises selling online before the pandemic (Ortiz-Chávez *et al.*, 2024), and delivery platforms expanded rapidly into the food and retail segments where in-person trade had been suspended (Economic Commission for Latin America and the

Caribbean, 2021). These technologies are cheap, transaction-level and contactless. They require no capital investment by the displaced worker and no reorganization of a firm.

Figure 2 shows the corresponding movement in firm-level digital margins. The sharpest increases between 2018 and 2022 occur in activities that were heavily restricted, accommodation and food above all, followed by retail and wholesale trade, while producer services moved only modestly. These patterns establish no causation on their own, but the activities recording the largest gains are the activities where restrictions bound hardest.

Figure 2: Peru: firm-level ICT adoption by economic activity, 2018 and 2022



Note: The figure reports the percentage of firms that maintained a website (Panel A) and made sales over the internet (Panel B) in reference years 2018 and 2022, for each of the 17 economic activities covered by INEI's firm-level survey. Activities are grouped according to the five-bin classification used in Section 2 (colored brackets on the right); within each bin, activities are ordered by 2018 website adoption. The firm universe comprises private firms with annual sales above 150 UIT; financial services and public administration are excluded. Source: INEI *Tecnologías de Información y Comunicación en las Empresas 2018, 2022* (Instituto Nacional de Estadistica e Informatica, 2019, 2024b), authors' calculations.

That the technology diffusing through Peru's informal economy was digital and organizational rather than capital-intensive is what the literature on innovation in infor-

mal economies would predict. de Beer *et al.* (2016) document that innovation among informal producers is incremental and adaptive, concerned with process and business model rather than with machinery. Ng'weno and Porteous (2018) make the complementary point about platforms, which bundle payment, matching and reputation services at low cost and in doing so both displace existing intermediation work and create new task-based work around themselves.

This reading also resolves an apparent tension with the closest existing evidence for Peru. Novella *et al.* (2023) find that firms adopting advanced network services subsequently reduced their demand for high-skill workers, an effect the pandemic amplified. Their result and ours concern different technologies acting on different populations: they identify registered firms that had already made substantial digital investments, for which further adoption displaced analytical work performed by employees, whereas the substitution we describe falls on routine in-person work, much of it performed by people with no employer at all.

2.4 Potential mechanisms

Restrictions on mobility can displace a worker in a routine, in-person occupation through at least three channels, and which of them operates depends on who employs that worker. Where the employer is a registered firm, the canonical account applies: an employer facing a binding constraint on the use of labor reorganizes production, and workers without contracts are the least protected margin of adjustment. Where the worker is own-account, there is no employer, and displacement operates through the substitution of digital transaction and delivery technologies for in-person exchange, adopted by consumers and downstream firms. Where the employer is a private household, neither applies, and the relevant channel is the withdrawal of demand for work performed inside other people's homes.

The three carry different implications that the data can speak to. Displacement con-

centrated among employees of registered firms in manufacturing and construction would point to the first; displacement concentrated among own-account workers in commerce and personal services to the second. In either case the effects should fall on workers at the bottom of the skill distribution rather than in its middle, since routine-intensive occupations in a developing economy are low-skill occupations, which is why polarization has not been found across developing countries (Maloney and Molina, 2019; Gasparini *et al.*, 2021) even though it is well documented in high-income ones (Autor *et al.*, 2003; Goos and Manning, 2007). They should also be larger for women, who are more exposed to automation risk in the region (Egana-delSol *et al.*, 2022a) and more likely to hold informal jobs over the life cycle (Berniell *et al.*, 2021).

The channels differ most usefully in their time profile. A pure interruption of demand should reverse when restrictions are lifted and workers return to their previous activity. Substitution of a technology for a task should persist, with recovery occurring through movement into different occupations rather than through resumption of the same one (Christenko, 2022). We do not observe technology adoption at the level of the individual worker, so we cannot identify which channel operates. What we can do is establish whether displacement occurred where these accounts predict, whether it persisted, and how workers recovered. Sections 4 and 5 take up each in turn.

3 Data and Variable Construction

We combine three sources: the panel component of the Peruvian National Household Survey (ENAHO), the Ministry of Labor's classification of industries by the severity of the restrictions they faced, and the OECD Programme for the International Assessment of Adult Competencies (PIAAC). The first provides the workers we follow, the second defines exposure to mobility restrictions, and the third defines exposure to automation risk.

3.1 Data sources and sample construction

ENAHO is Peru's largest official household survey. It collects data on employment, labor earnings, occupation, industry and socio-demographic characteristics, and its rotating design allows the same households to be revisited once a year for up to five years. We use the panel component covering 2018 to 2021, in which nearly every worker in our sample is observed in each of the four years. INEI aims to revisit each household in the same month it was first interviewed, so a worker's observations typically fall in the same quarter year after year. We date each observation by the quarter in which it was taken, which lets us follow the sample at quarterly frequency.

We restrict attention to workers observed employed in 2019, the year from which we assign industry and occupation, and aged 22 to 70. This yields 5,471 workers followed across four years. Our two outcomes are an indicator for being employed and the logarithm of hourly labor earnings, both measured quarterly.[2]

Attrition is low, at 2.9 percent, and does not concentrate in any analytical group. It is similar across paralyzed and essential industries, across high and low automation risk occupations, and across subgroups defined by gender, firm size, skill level and sector (Table A.1). We therefore do not expect attrition to bias the estimates.

3.2 Paralyzed and Essential Industries

Based on the economic reactivation plan described in section 2, the Ministry of Labor and Promotion of Employment (MTPE, for its acronym in Spanish) built a classification for 417 industries at the ISIC four-digit level, classifying industries by a measure of severity of the restrictions to operate that such economic activity would face[3]. This allows us

[2]Labor earnings are deflated yearly to real terms with 2021 as the base year and adjusted by a spatial deflator that accounts for area of residence (urban and rural) and regional cost-of-living differences, so that earnings are expressed in terms of the capital city's cost of living. We use the official temporal and spatial deflators that Peru's National Institute of Statistics and Informatics (INEI, for its acronym in Spanish) constructs for use with ENAHO.

[3]The MTPE (2022) elaborated this classification based on the initial list of essential activities described in Decreto Supremo No. 044-2020-PCM. It then reviewed its classification following closely the progres-

to distinguish activities to be exempted from mobility restrictions in all of the lockdown stages to those that faced some level of restriction (MTPE, 2022). Table A.2 shows the average monthly number of formal private workers in 2021 and the proportion of workers that are classified as essential or paralyzed within economic sector group. This type of classification has been widely used to estimate the labor-market impact of pandemic-related restrictions, not only in Peru (MTPE, 2020, 2021a,b) but also in other countries (for example, Casarico and Lattanzio, 2022; Meekes *et al.*, 2020).

We used the MTPE classification to categorize workers in the ENAHO into two groups based on their pre-pandemic 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. Naturally, we limited our analysis to individuals who were employed in 2019.

3.3 Automation Risk

Typically, jobs that involve routine, repetitive, and well-defined tasks are more likely to be replaced by different types of labor-saving technologies (Acemoglu and Autor, 2011; Autor, 2013; Goos *et al.*, 2014; Frey and Osborne, 2017; Acemoglu and Restrepo, 2020, 2019). Since this paper does not measure technology adoption directly, we remain agnostic to the specific types of technologies that may have been adopted during the mobility restrictions shock.

Following Gasparini *et al.* (2021), we construct a routinization task content index (RTI) from PIAAC, which records the tasks Peruvian workers perform. A job is routine-task-intensive if it does not involve any of the following at least once a week: (i) managing or supervising others, (ii) planning others' activities, (iii) confronting problems, or (iv) writing articles or reports. The RTI for an occupation is the share of its workers whose jobs

siveness of how economic activities were resumed, as stated in the four phases plan, and assigned ISIC codes values equal to 0 if the activity was never restricted ("essential") and values of 0.25, 0.50, 0.75, and 1.00 if activities were resumed during phases 1 through 4. See Table A.2 for a more detailed description.

meet that definition. We compute it at the two-digit ISCO level, at which 41 occupation groups appear in our data, and link it to each worker's 2019 occupation in ENAHO.[4]

We classify as at high automation risk those workers whose 2019 occupation has an RTI at or above the median of the index in our estimation sample, which is 0.778. Seven occupation groups clear this threshold: skilled agricultural workers, subsistence farmers, agricultural and fishery laborers, cleaners and helpers, laborers in mining, construction, manufacturing and transport, food preparation assistants, and street vendors. They account for 50.1 percent of the workers we follow but 36.3 percent of weighted employment, since high-routine occupations concentrate in rural areas that ENAHO over-samples. All remaining occupations are classified as at low automation risk.

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.

[4]PIAAC records occupation in two variables of differing coverage. Where the more detailed one is missing we use the coarser one, which recovers about a tenth of Peruvian respondents, concentrated in high-routine groups. Omitting them would understate routine task content in precisely the occupations the index is meant to identify.

3.4 The estimation sample

Of the 5,471 workers we follow, 2,620 (47.9 percent) worked in a paralyzed industry in 2019 and 2,742 (50.1 percent) held an occupation at high automation risk. The intersection, the treated group, is 644 workers, 11.8 percent of the sample and 15.0 percent of weighted employment. Table A.3 reports the composition of each group by gender, firm size, formality, skill level and sector, together with average hourly labor earnings. Workers in paralyzed industries are more formal, more skilled and better paid than those in essential industries, and concentrate in manufacturing, retail and services. Workers at high automation risk are the reverse: predominantly informal, less skilled, lower paid, and concentrated in agriculture and mining. The treated group combines both profiles and contains a greater share of women and of workers with low and medium skill levels.

We measure informality with the variables INEI constructs and distributes with ENAHO. Table 2 applies the three categories introduced in Section 2 to the four cells of the design. The treated group is considerably more informal than the workers it is compared against: 87.0 percent hold informal jobs, against 53.0 percent of workers in the same paralyzed industries holding low risk occupations. The excess lies in unregistered production units, which account for 56.5 percent of treated employment against 39.4 percent among paralyzed low risk workers. The second informal category is larger in the treated cell, at 30.5 against 13.5 percent, but two thirds of it there consists of domestic workers in private households, whereas among paralyzed low risk workers it is almost entirely employment in registered enterprises.[5]

The two high automation risk cells draw on almost disjoint sets of occupations. High routine task content resolves in the Peruvian occupational structure to elementary occupations together with skilled agricultural work, and the two cells divide that set between

[5]Domestic workers account for 66.4 percent of the category in the paralyzed high risk cell, 2.1 percent in the paralyzed low risk cell, and none in either essential cell. Netting them out, employment in registered enterprises without social security is about 10 percent of the treated cell and 13 percent of the paralyzed low risk cell.

Table 2: Employment and informality by paralyzation status and automation risk, 2019

	Employment			Share of cell employment (%)			
	n	000s	%	Informal	In informal sector	Outside inf. sector	Formal
Essential, low risk	753	2,461.0	16.60	53.15	42.81	10.34	46.85
Essential, high risk	2,098	3,157.1	21.30	96.58	94.23	2.35	3.42
Paralyzed, low risk	1,976	6,980.6	47.09	52.97	39.42	13.54	47.03
Paralyzed, high risk	644	2,225.3	15.01	87.03	56.54	30.49	12.97
All employed	5,471	14,823.9	100.00	67.40	54.23	13.17	32.60

Note: ENAHO panel estimation sample: 5,471 workers employed in 2019 and aged 22 to 70, tracked from 2018 to 2021, weighted by the panel expansion factor. High automation risk denotes a routinization task content index at or above 0.778, the median of the index in the estimation sample; paralyzed industries are those with non-zero shutdown severity in the MTPE classification. Following the International Labour Organization's Seventeenth ICLS resolution, informal employment comprises jobs without social security protection and is divided according to whether the employing production unit belongs to the informal sector, meaning an unincorporated household enterprise that is neither registered nor keeps formal accounts. The two informal columns sum to the informal column, and the informal and formal columns sum to 100. Employment in private households is classified outside the informal sector, since a household is not an informal sector production unit; domestic workers account for 66.4 percent of that category in the paralyzed high risk cell, 2.1 percent in the paralyzed low risk cell, and none in either essential cell. Panel weights represent workers traceable across all four years rather than the 2019 employed population, which is why the overall informality rate here differs from INEI's published 2019 figure of 72.7 percent.

them. Among essential industries the high risk cell is 98.7 percent agricultural. Among paralyzed industries it is 98.9 percent urban elementary: cleaners and helpers, laborers in mining, construction, manufacturing and transport, street vendors, and food preparation assistants (Table A.4). The comparison therefore relies on agricultural workers in essential industries providing a valid counterfactual trajectory for urban elementary workers in paralyzed ones, an assumption we take up in Section 4.

The treated group is mixed in its employment relationships, and the mix bears on the channels set out in Section 2. Across the sample, 63.4 percent of workers are not wage employees of another party: they are employers, own account workers, or unpaid workers in family production units. That share reaches 84.5 percent in the essential high risk cell, which is own account and family agriculture almost throughout. The treated group is the most employee-like of the four cells, at 42.1 percent, and divides into three comparable blocs: manual wage workers at 36.2 percent, own account workers at 37.6 percent, and domestic workers employed by private households at 18.2 percent (Table

A.5).

Finally, both treatment dimensions track visible movements in employment within the sample itself. Figure A.1 plots quarterly employment among workers in paralyzed and essential industries, indexed to 2019. The two series move closely together through 2018 and 2019, including the shared seasonal dip in the fourth quarter of 2018, and both peak at their 2019 level before the pandemic. They separate sharply in the second quarter of 2020: employment among workers in paralyzed industries falls to 55 percent of its 2019 level while essential employment falls to 88 percent. Paralyzed employment recovers through 2021 without closing the gap. Figure A.2 restricts attention to paralyzed industries and splits them by automation risk. Here too the two series track each other through 2019, and both fall in 2020, but the decline is deeper for high automation risk occupations, to 43 percent of their 2019 level against 59 percent for low risk occupations, and the subsequent recovery leaves them further below their pre-pandemic level. Neither figure identifies anything on its own, since both mix changes in employment with changes in the composition of who is working. They establish that the distinctions we exploit correspond to divergences that appear in 2020 rather than continuing trends already underway, and Section 4 takes up the identification question directly.

4 Empirical strategy

Our identification strategy exploits the exogenous timing of the pandemic and the pre-pandemic allocation of workers across essential and non-essential industries and across occupations at high or low automation risk to estimate the impact of mobility restrictions on both the probability of being employed and hourly labor earnings.[6] To guide the empirical analysis, we begin from a fully saturated difference-in-differences and triple-

[6]Labor earnings are deflated as described in Section 3. Non-employed workers are assigned zero earnings, and we take $\ln(w+1)$ to accommodate these zeros. As a robustness, we also use two alternative treatments of zero earnings, the inverse hyperbolic sine transformation and a sample restricted to workers who remain employed.

differences framework and then show how these models are implemented using fixed effects.

$$y_{ikq} = \beta_0 + \beta_1 Post_q + \beta_2 Paralyzed_k + \delta_1 (Post_q \times Paralyzed_k) + \varepsilon_{ikq}. \tag{1}$$

$$y_{igq} = \beta_0 + \beta_1 Post_q + \beta_3 HighRisk_g + \delta_2 (Post_q \times HighRisk_g) + \varepsilon_{igq}. \tag{2}$$

$$\begin{aligned} y_{igkq} = {} & \beta_0 + \beta_1 Post_q + \beta_2 Paralyzed_k + \beta_3 HighRisk_g \\ & + \delta_1 (Post_q \times Paralyzed_k) + \delta_2 (Post_q \times HighRisk_g) + \delta_3 (Paralyzed_k \times HighRisk_g) \\ & + \delta_4 (Post_q \times Paralyzed_k \times HighRisk_g) + \varepsilon_{igkq}. \end{aligned} \tag{3}$$

$Post_q$ is an indicator equal to one for quarters after the onset of the pandemic and zero otherwise. $Paralyzed_k$ is a time-invariant indicator equal to one for workers whose 2019 industry was classified as paralyzed and zero for workers whose 2019 industry was classified as essential. Likewise, $HighRisk_g$ is a time-invariant indicator equal to one for workers whose 2019 occupation was classified as highly automatable and zero otherwise.

In the first model, y_{ikq} denotes the outcome of interest (employment-status dummy or hourly labor earnings) for individual i in quarter q and industry k.[7] The coefficient δ_1 is the standard difference-in-differences estimate and captures the differential change in the outcome after the onset of the pandemic between workers in paralyzed industries and those in essential industries.

In the second model, y_{igq} is the outcome variable for individual i in quarter q and occupation g. The coefficient δ_2 is also a standard difference-in-differences estimate and captures the differential change in the outcome after the onset of the pandemic between workers in high-risk and low-risk occupations.

The third model combines both dimensions in a triple-differences specification. In

[7] Industry and occupation classifications correspond to the 2019 observation.

Equation 3, β_1 captures the average post-pandemic change for the baseline group, β_2 the baseline difference between paralyzed and non-paralyzed industries, and β_3 the baseline difference between high- and low-risk occupations. δ_1 captures the average differential post-pandemic effect for workers in paralyzed industries relative to workers in non-paralyzed industries, while δ_2 captures the average differential post-pandemic effect for workers in high-risk occupations relative to workers in low-risk occupations. The coefficient δ_3 captures baseline differences between high-risk occupations across paralyzed and non-paralyzed industries prior to the pandemic.

δ_4 is the coefficient of main interest. It captures whether, after the onset of the pandemic, employment or labor earnings fell more for workers in highly automatable occupations when they were employed in industries affected by mobility restrictions than for otherwise comparable workers in industries that were not. This is the key coefficient for our research question because it separates the effect of mobility restrictions on highly automatable jobs from two broader patterns: the overall impact of the pandemic on paralyzed industries, and the overall difference in how high- and low-risk occupations evolved during the pandemic. In other words, δ_4 asks whether highly automatable jobs deteriorated disproportionately precisely in the industries where mobility restrictions were binding. A negative δ_4 is therefore consistent with pandemic-related restrictions generating labor-market adjustments associated with automation risk.

We implement these models using the following two-way fixed-effects specifications:

$$y_{ikq} = \phi_k + \lambda_q + \delta_1(Post_q \times Paralyzed_k) + \varepsilon_{ikq}. \tag{4}$$

$$y_{igkq} = \phi_k + \lambda_q + \alpha HighRisk_g + \delta_2(Post_q \times HighRisk_g) + \varepsilon_{igkq}. \tag{5}$$

$$
\begin{aligned}
y_{igkq} = \phi_k + \lambda_q + \alpha HighRisk_g \\
&+ \delta_1(Post_q \times Paralyzed_k) + \delta_2(Post_q \times HighRisk_g) + \delta_3(Paralyzed_k \times HighRisk_g) \\
&+ \delta_4(Post_q \times Paralyzed_k \times HighRisk_g) + \varepsilon_{igkq}.
\end{aligned} \tag{6}
$$

Here, ϕ_k and λ_q denote industry and quarter fixed effects, respectively. Quarter fixed effects absorb the standalone post-pandemic term $Post_q$, while industry fixed effects absorb the standalone term $Paralyzed_k$, since paralyzed status is defined at the industry level and is time-invariant. Because we do not include occupation fixed effects in the baseline specification, the standalone term $HighRisk_g$ remains in Equations 5 and 6. Thus, the coefficients of interest in the implemented models retain the same interpretation as in the fully saturated framework.

The advantage of these specifications is that fixed effects absorb time-invariant industry heterogeneity and common quarter-specific shocks, thereby increasing precision in the estimates. We do not include occupation fixed effects in the baseline specification in order to preserve the cross-occupation variation in automation risk that is central to our identification. However, Appendix Table A.6 shows that the estimates are very similar when occupation fixed effects are included. The table also shows that the results are robust to estimating the fully saturated specification and to including additional fixed-effects structures, such as individual fixed effects, though the triple-difference coefficient loses statistical significance once interacted year-industry fixed effects are included (discussed further in the Robustness subsection below).

This methodology assumes the absence of other within-industry factors that might confound automation risk and its impact on labor outcomes. A potential source of concern is that some occupations may have had a greater ability to adapt to remote work than others. If the feasibility of remote work is correlated with automation risk, this could bias the estimation. To address this concern, we conduct additional robustness checks that assess this possibility. This will be explained in more detail in the following sections.

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 similarly to that of control workers. To assess the validity of this parallel-trends assumption in our triple-differences setting, we estimate the following dynamic triple-differences equation:

$$\begin{aligned} y_{igkq} = \phi_k + \lambda_q + \alpha HighRisk_g \\ + \sum_{j \neq q_0} \delta_{1j}(\gamma_j \times Paralyzed_k) + \sum_{j \neq q_0} \delta_{2j}(\gamma_j \times HighRisk_g) \\ + \delta_3(Paralyzed_k \times HighRisk_g) \\ + \sum_{j \neq q_0} \delta_{4j}(\gamma_j \times Paralyzed_k \times HighRisk_g) + \varepsilon_{igkq}. \end{aligned} \tag{7}$$

Here, γ_j denotes dummy variables for each quarter j in the set Q (2018Q1–2021Q4, excluding the baseline quarter $q_0 = 2019Q4$). The coefficients δ_{1j}, δ_{2j}, and δ_{4j} measure the dynamic effects in quarter j relative to the omitted quarter. If the estimated coefficients δ_{4j} are statistically insignificant for pre-pandemic quarters, the parallel-trends assumption is more likely to hold.

5 Results

5.1 Main Results

Table 3 summarizes the results from estimating equations 4, 5, and 6 for employment status (Models 1–3) and hourly labor earnings 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 contrasting patterns for workers in high-risk jobs in general (whether paralyzed or not): employment does not change significantly relative to low-risk jobs after the pandemic (Model 1), while labor earnings increase by 0.553 log points relative to low-risk jobs (Model 4, significant at the 10% level). This asymmetry probably reflects the higher share of high-risk jobs in essential industries (about 77% in 2019) than in paralyzed industries (about 23%).

Second, Model 2's estimates indicate that COVID-19-related restrictions resulted in an 8.7 percentage-point larger decline in employment in paralyzed industries relative to essential industries, while Model 5 shows a similar trend for labor earnings, with a relative decrease of approximately 59.5%. 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 12.2 percentage points higher than for other jobs. This represents a contraction of 13.5%, based on a reference employment rate of 90.1% in the pre-treatment period (2018Q1-2020Q1) for the high-risk paralyzed group. Similarly, the triple-difference coefficient from Model 6 was -1.021, indicating that hourly labor earnings decreased 64.0% more for highly automatable jobs in industries affected by mobility restrictions than for other jobs. The earnings result is similar under an alternative transformation that accommodates zero earnings (Table A.7). Using the inverse hyperbolic sine transformation yields a similarly large and significant decline (-67.6%). By contrast, restricting the sample to workers who remain employed—thereby isolating the intensive margin—yields a much smaller and statistically insignificant effect (-9.6%). This suggests that the earnings effect operates mainly through the extensive margin, that is, workers who lose their jobs entirely, rather than through earnings cuts among those who remain employed.

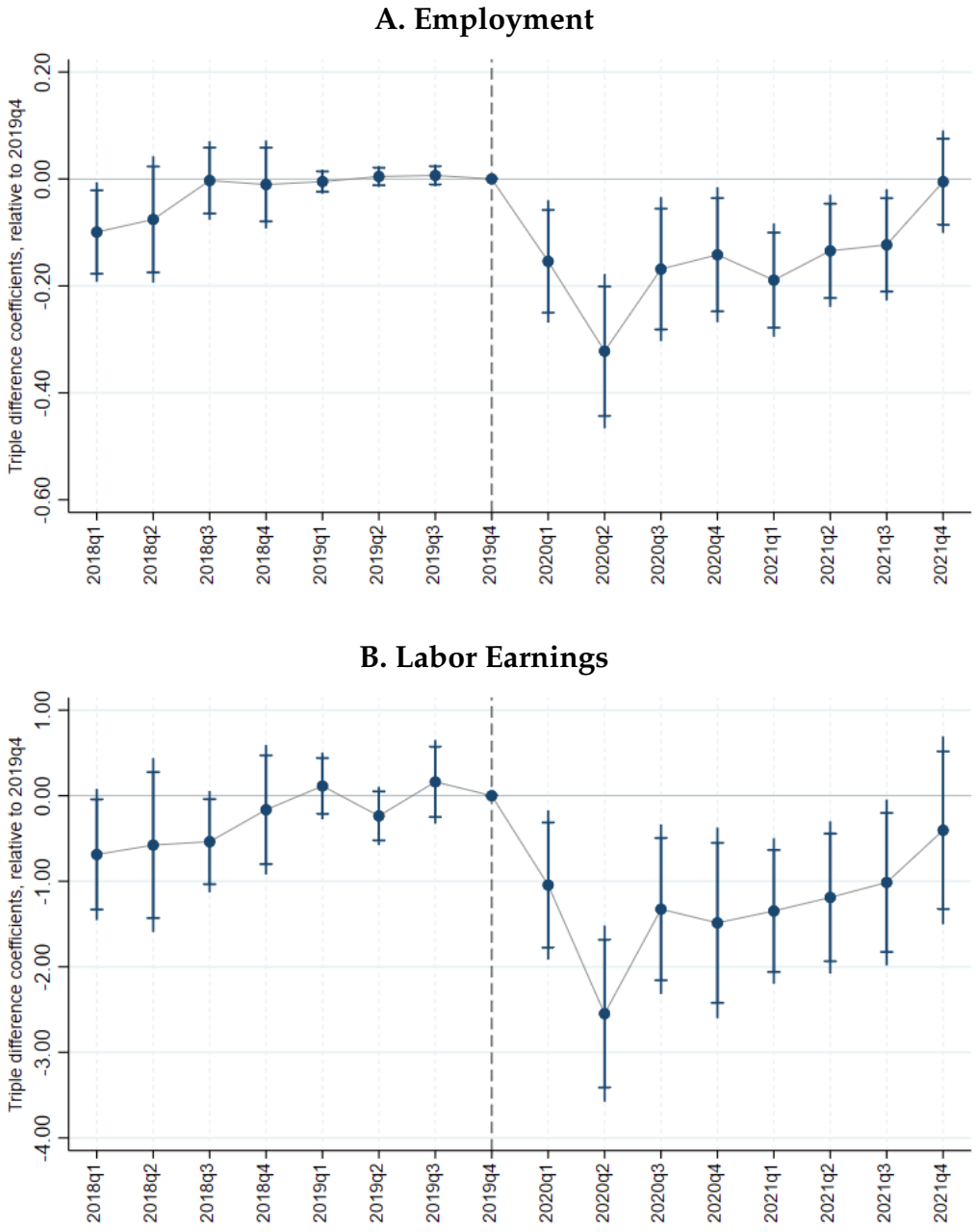
Table 3: Effect of mobility restrictions and automation risk on the labor market

	Employment			Labor Earnings (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post * High Aut Risk	0.0380		0.0506**	0.553*		0.621***
	(0.0332)		(0.0219)	(0.327)		(0.209)
Post * Paralyzed		-0.0869***	-0.0322		-0.903***	-0.347**
		(0.0239)	(0.0238)		(0.235)	(0.168)
Post * High Aut Risk * Paralyzed			-0.122***			-1.021***
			(0.0324)			(0.260)
Observations	21719	21719	21719	21719	21719	21719
Adjusted R^2	0.103	0.107	0.110	0.133	0.132	0.140

Note: This table displays the estimation of Equations 4, 5, and 6 for the employment-status dummy (columns 1–3) and the logarithm of labor earnings (columns 4–6) using data from 2018 to 2021. High automation risk is defined as workers with a routinization-task-content index at or above the sample median. All regressions include industry, and quarter fixed effects. We estimated high-dimensional fixed effects following Correia *et al.* (2016). Clustered robust standard errors at the industry 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 generated labor-market adjustments consistent with automation-related substitution. 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 7. As shown in Figure 3 (Panels A and B), computed quarterly, most point estimates for pretreatment quarters are not significant at either the 90% or 95% confidence level; the exception is 2018Q1 for employment, which sits close to the edge of the 90% band. If anything, the pre-treatment coefficients trend slightly upward between 2018Q1 and 2019Q3 rather than downward, which would work against finding the negative post-treatment effects we document. Overall, this provides limited evidence against the parallel-trends assumption.

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

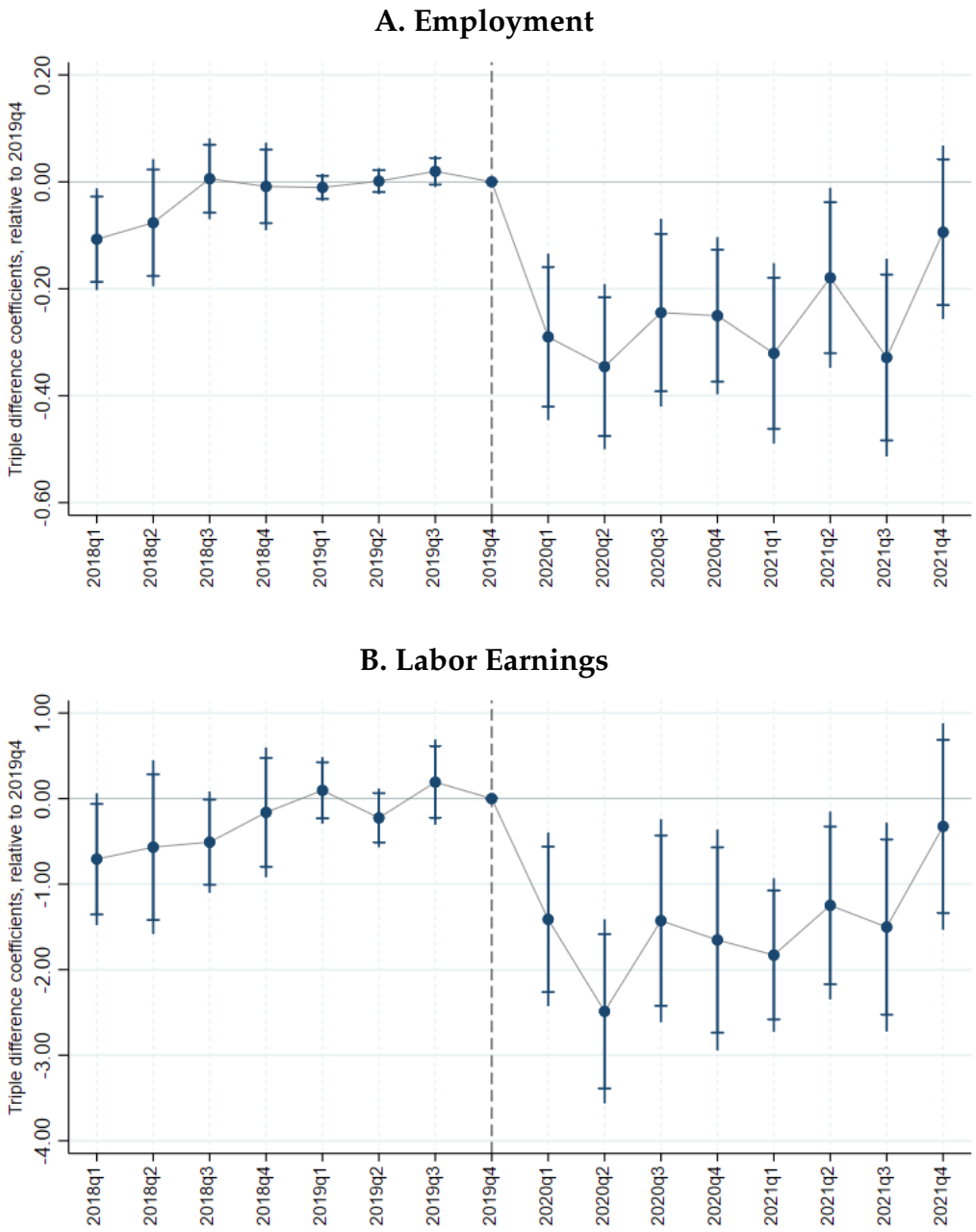


Note: The figure shows quarterly point estimates, along with the 90% and 95% confidence intervals of the dynamic triple-difference equation described in Equation 7 for the employment-status dummy (Panel A) and the logarithm of labor earnings (Panel B) using data from 2018 to 2021. High automation risk is defined as workers with a routinization-task-content index at or above the sample median. Standard errors are clustered at industry level.

Quarterly estimates allow us to observe that workers at high risk of automation had lower employment rates and hourly labor earnings up to 18 months after the pandemic outbreak. Afterward, these workers' employment rates and labor earnings 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 to low-risk occupations is excluded. By contrast, when occupational mobility in the opposite direction (from low-risk to high-risk) is excluded (Appendix Figure A.3), the recovery path observed in the baseline estimation remains. This evidence suggests that employment recovery was primarily driven by occupational mobility from high-risk to low-risk jobs.

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



Note: The figure shows quarterly point estimates, along with the 90% and 95% confidence intervals of the dynamic triple-difference equation described in Equation 7 for the employment-status dummy (Panel A) and the logarithm of labor earnings (Panel B) using data from 2018 to 2021 and not including workers that moved from high- to low-risk jobs after 2020: in Panel A, these workers are recoded as not employed in the quarters after the switch; in Panel B, they are dropped from the sample in the quarters after the switch. High automation risk is defined as workers with a routinization-task-content index at or above the sample median. Standard errors are clustered at the industry level.

5.2 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. Additionally, we explore the extent to which certain confounding shocks can affect our estimates. The results are shown in Table A.8 from the Online Appendix.

A concern in our baseline analysis is that the control group, defined as workers below the median RTI, may not be completely unaffected by automation shocks. Workers just below the median, while less exposed to automation than those well above it, may still experience some automation-related changes. If this is the case, the estimates could understate the effects associated with automation risk by attenuating the contrast between treatment and control groups.

To address this concern, we re-estimated the model using the RTI as a continuous measure rather than a binary threshold (Column 2 from Online Appendix Table A.8). This approach captures the full gradient of automation risk across occupations, rather than relying on a single cutoff to separate treatment from control. The results remain statistically significant, with a one standard deviation increase in the RTI (0.17 points) associated with a reduction in employment of 4.5 percentage points.

Next, we constructed an alternative RTI following Gasparini *et al.* (2021) (Column 3). In addition to the original criteria, this measure classified jobs as routine-intensive if they did not involve (i) calculating budgets or costs or (ii) giving presentations. The coefficients derived using this alternative definition are smaller in magnitude than the baseline but remain statistically significant for both employment (-0.071 vs. -0.122) and labor earnings (-0.763 vs. -1.021), maintaining the same sign as the baseline.

To further test the robustness of our findings, we used an alternative measure of automation risk based on the Frey and Osborne (2017) estimates (Column 4). Under this specification, the coefficients are substantially smaller in magnitude and no longer statistically significant for either employment (-0.007 vs. -0.122 in the baseline) or labor earn-

ings (-0.487 vs. -1.021), though both retain the baseline's negative sign. As discussed in Section 3.3, the FO measure was estimated on US-specific occupational descriptions and does not capture within-occupation task heterogeneity, which may explain its weaker fit to the Peruvian context.

Another concern is that many workers in developing economies, including Peru, are engaged in unpaid family work (11% of our sample in 2019). A worry is that automation is conceptually more diffuse for these workers, as it usually presumes a firm deciding whether to substitute tasks performed by workers with technology to cut production costs, a decision margin that is more ambiguous for workers not receiving pay. We estimated a version of our baseline specification excluding the segment of workers that in 2019 were unpaid family workers. The coefficients on employment and labor earnings barely move (Column 5, Table A.8), indicating that our results are not driven by this segment of the labor force.

We also estimated the model including interacted year-industry fixed effects (Column 6 from Appendix Table A.8). The objective is to net out industry-specific shocks, unrelated to automation, that vary from year to year and could otherwise be confounded with the paralized-industry treatment. Specifically, the estimated model is given by

$$\begin{aligned} y_{igkq} = \phi_k + \lambda_q + \varphi_{kt} + \alpha HighRisk_g \\ + \delta_1 \left(Post_q \times Paralyzed_k\right) + \delta_2 \left(Post_q \times HighRisk_g\right) \\ + \delta_3 \left(Paralyzed_k \times HighRisk_g\right) + \delta_4 \left(Post_q \times Paralyzed_k \times HighRisk_g\right) + \varepsilon_{igkq}. \end{aligned} \tag{8}$$

where φ_{kt} absorbs the interacted year (t) $\times$ industry (k) fixed effects, adding 449 additional coefficients to the baseline specification. This is a demanding specification: saturating the model with a separate fixed effect for every industry-year combination can net out unobserved shocks specific to an industry in a given year, but at the same time

absorbs much of the variation that identifies the treatment interaction itself. Once these fixed effects are included, the triple-difference coefficient falls well short of statistical significance and its magnitude drops substantially: for employment, from -0.122 in the baseline to -0.037; for hourly labor earnings, from -1.021 to -0.284. This attenuation could reflect either industry-specific shocks that the baseline specification fails to capture, or the cost of reducing identifying variation once industry and year are jointly saturated. Although our data cannot fully distinguish between these two explanations, Table A.8 from the Online Appendix shows that the results are stable across other alternative fixed-effect structures we consider, including worker-level and occupation fixed effects, with the interacted year-industry specification being the one exception.

Finally, we checked that our estimates were not influenced by confounding factors, such as a shift to teleworking (Columns 7 and 8). If mobility restrictions led to some jobs being performed remotely, and if a job's potential for remote work is correlated with its exposure to automation, then the observed decline in automatable jobs might be influenced by their teleworkability. To address this concern, we developed an index measuring the potential for remote work at the occupational level, and re-estimated the main specifications for subsamples of jobs with similar degrees of the index.

Using OECD PIAAC data, we classified a job as 'teleworkable' if it involves frequent computer use and does not require regular, prolonged physical activity. Then, the teleworkability index was calculated as the share of jobs at the occupational level that can be performed remotely. We linked this index to the ENAHO, assigning each worker a value based on their 2019 occupation.

We binarized the index, classifying workers as eligible for telework if they scored above the index's median, and as less eligible for telework if they scored below. Subsequently, we estimated our main specification separately for each group. The results, presented in the last two columns of Table A.8 in the online Appendix, show negative point estimates of similar magnitude in both groups, though statistical significance dif-

fers by outcome and subgroup, likely reflecting the smaller size of each subsample: for employment, the effect is significant among more-telework-eligible workers (-0.220) but not among less-eligible workers (-0.268); for labor earnings, the pattern is reversed, with significance only among less-eligible workers (-1.776). We conclude from this that the shift to remote work does not appear to be driving our main results.

5.3 Heterogeneous Effects

This subsection analyzes the results of the main specification for different subsamples. We estimate the triple-difference models for employment and labor earnings by gender, firm size, formality, skill level, and urban/rural division. We suspect that women, small and medium-sized firms, less-skilled workers, and informal workers in urban areas 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 the effects associated with automation risk on employment and labor earnings are largest in magnitude among medium-skilled individuals (defined as those who possess technical education), followed by high-skilled workers (those with higher education) and then low-skilled workers (with no education or only high school education); point estimates are negative for both employment and labor earnings across all three groups. Because the effect does not appear to be confined to the middle of the skill distribution, this pattern is, at most, modestly suggestive of the absence of labor-market polarization documented elsewhere in developing countries (Gasparini *et al.*, 2021; Brambilla *et al.*, 2022; Maloney and Molina, 2019; Lewandowski, 2017), in contrast to developed economies, where automation-related displacement is typically concentrated among medium-skilled workers while higher- and lower-skilled workers are comparatively protected (Autor *et al.*, 2003; Goos and Manning, 2007).

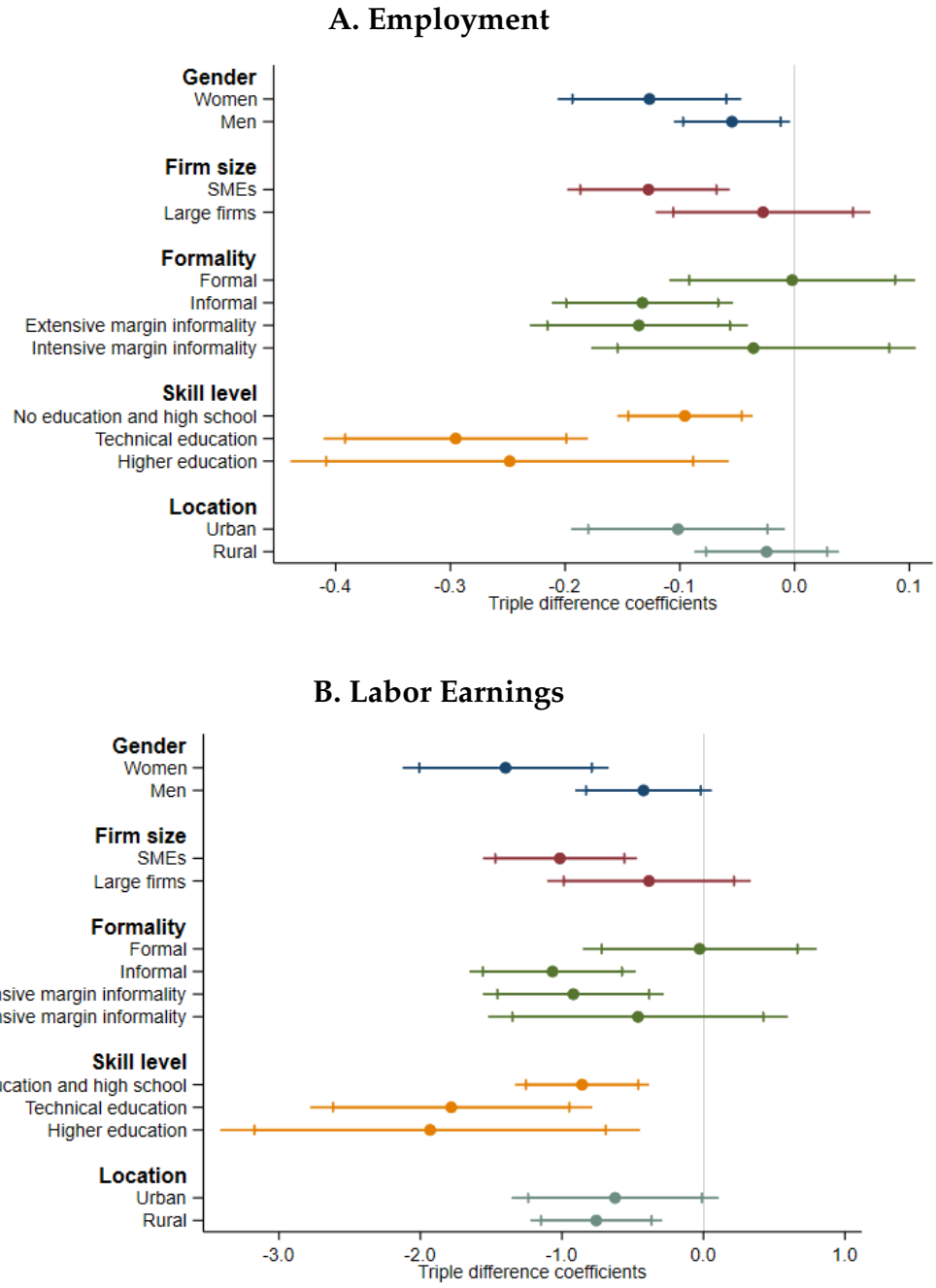
In addition, the effects are especially significant for informal workers and for small and medium-sized firms, defined as businesses employing fewer than 100 workers. These

patterns are consistent with informal and small firms reorganizing production in response to mobility restrictions, as well as with broader changes in the use of digital technologies. Within informality, the effect is concentrated in the extensive margin, that is, informal workers employed in informal firms, rather than the intensive margin. This is consistent with informal firms adopting basic forms of technology, and with informal self-employed workers being indirectly displaced by the growing adoption of digital payment channels and e-commerce.

Furthermore, results suggest that women are more affected than men, which may partly reflect women's higher levels of informality.

Finally, the results by urban/rural location show that the employment effect is concentrated in urban areas, where mobility restrictions were most binding, while the corresponding estimate in rural areas—dominated by essential, largely unrestricted agricultural activity—is close to zero and not statistically significant. Labor earnings effects, however, are also significant in rural areas, similar in magnitude to the urban estimate.

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



Note: This figure presents the triple-difference coefficient estimated from Equation 6, along with the 90% and 95% confidence intervals for the employment-status dummy (Panel A) and the logarithm of labor earnings (Panel B), using data from 2018 to 2021 for various subsamples by gender, firm size, formality status, skill level, and location. High automation risk is defined as workers with a routinization-task-content index at or above the sample median. Standard errors are clustered at the industry level.

6 Policy Implications and Concluding Remarks

This paper examines how mobility restrictions during the COVID-19 pandemic affected labor market outcomes across occupations with different exposure to automation risk. Restrictions imposed on workers' mobility and in-person interactions during the pandemic represented a natural experiment to explore these dynamics. By constraining the use of labor, these restrictions may have created incentives for firms to reorganize production and reduce reliance on routine, in-person tasks, while seeking alternative ways to maintain production. Using Peru as a case study, we draw on a large rotating household panel to identify jobs more vulnerable to technology-related substitution. 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 operating. Additionally, we leveraged variation in occupational exposure to automation risk. Our empirical methodology consisted of comparing post-pandemic changes between workers in high and low automation risk occupations across industries differentially exposed to mobility restrictions, a classification based on a routine-task-intensity index.

The results show that mobility restrictions were associated with larger employment and labor-earnings declines in jobs at higher risk of being automated. Additionally, we document that high-risk workers affected by the restrictions 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. Importantly, the results are robust to a range of alternative specifications and measures of automation risk, and a shift to teleworking does not appear to drive the main findings.

We also find strong heterogeneous effects, with impacts concentrated among women, informal workers, and small and medium-sized firms, and present across the skill distribution, with the largest effects among medium-skilled individuals. These patterns

are broadly consistent with evidence from other Latin American countries showing that employment in highly automatable occupations declined more strongly in sectors most affected by pandemic-related restrictions, as shown by Egana-delSol *et al.* (2022b) and Bonilla-Mejía *et al.* (2023). In both studies, the authors find that employment in occupations with high probabilities of being automated and in industries more severely affected by the economic shutdown fell during and after the pandemic period.

To interpret these results, it is useful to consider the nature of technology adoption in Peru. Using the ENHAT survey, Novella *et al.* (2023) show that the adoption of new technologies prior to the pandemic was still limited and concentrated in specific types of firms, with a focus on digital and network-based technologies. They also document that technology adoption is associated with changes in labor demand. In this context, our findings suggest that firms may adjust along task and occupational margins when faced with constraints on labor availability, even in settings where large-scale automation investments are limited. Our results do not establish that firms adopted automation technologies during the pandemic. Rather, they show that restrictions on labor mobility disproportionately affected workers performing tasks that were more susceptible to technological substitution.

These results point to broader dynamics that extend beyond the COVID-19 context. Shocks that constrain labor availability can interact with the task content of jobs and generate uneven effects across workers. In economies such as Peru, where informality is widespread and many workers are employed in small firms, these effects may reinforce existing labor-market vulnerabilities. The recovery patterns documented in the paper also suggest that part of the adjustment can occur through occupational reallocation: workers initially exposed to the largest employment losses subsequently recovered in part by moving toward occupations with lower automation risk.

These findings carry several policy implications, centered on the costs that mobility restrictions impose across different types of jobs and workers, and on the adjustment that

follows such restrictions.

First, the results highlight that mobility restrictions can generate substantially different labor-market costs depending on the task content of jobs. When restrictions on mobility or in-person activity are necessary, accompanying economic policies should therefore account not only for differences across industries but also for differences in workers' ability to continue performing their tasks. Workers in routine-intensive and highly automatable occupations may face particularly large employment losses even relative to other workers in the same industry. This suggests a role for temporary support during episodes in which access to workplaces is severely constrained, targeted toward workers most exposed to the labor-market effects of such restrictions.

Second, the concentration of effects among informal workers, women, and workers in small and medium-sized firms, together with the heterogeneous effects across the skill distribution, suggests that the costs of mobility restrictions can fall disproportionately on groups with limited capacity to absorb temporary employment shocks. In economies with high informality, emergency income support and social-protection mechanisms that can reach workers outside traditional employer-based systems may therefore be particularly important when restrictions on economic activity are imposed.

Third, the subsequent recovery of employment among high-risk workers through movements toward lower-risk occupations points to the importance of facilitating occupational reallocation following large disruptions. Job-search assistance, information about opportunities across occupations, and reskilling (for example, Nedelkoska and Quintini, 2018) can help reduce the adjustment costs faced by workers whose previous tasks become less viable following a shock. In this sense, training policies are relevant not as a general response to automation, but as part of the policy toolkit for facilitating worker transitions after shocks that interact with the task content of employment.

Finally, the results underscore a broader consideration for policy responses to mobility restrictions during pandemics and other emergencies. Policies aimed at protecting public

health may have unavoidable economic costs, but those costs need not be distributed uniformly. Accounting ex ante for differences in occupational vulnerability could allow governments to complement necessary restrictions with support directed toward workers most exposed to the resulting labor-market consequences.

Overall, the results suggest that even in labor-abundant developing economies, shocks that disrupt the availability or use of labor can reshape how work is allocated across tasks and occupations beyond the initial disruption. The experience of Peru shows that the labor-market consequences of mobility restrictions depend importantly on the characteristics of the jobs held by affected workers. Understanding these dynamics is important for designing complementary policies that mitigate the unequal labor-market consequences of mobility restrictions and facilitate workers' subsequent reallocation.

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Online Appendix

A. Online Figures and Tables

Table A.1: Attrition statistics

	Attrited Observations	Total Observations	Attrition Rate
All workers	157	5471	2.9
Paralyzation and Automation Risk			
Paralyzed	97	2620	3.7
Essential	60	2851	2.1
High Automation Risk	63	2742	2.3
Low Automation Risk	94	2729	3.4
Paralyzed and High Aut Risk	25	644	3.9
Gender			
Women	49	2737	1.8
Men	108	2734	4.0
Firm Size			
Small and Medium Firms	128	4584	2.8
Large Firms	29	887	3.3
Formality			
Formal	42	1277	3.3
Informal	115	4194	2.7
Skill Level			
Low-Skilled	117	4414	2.7
Medium-Skilled	22	499	4.4
High-Skilled	18	558	3.2
Sector			
Agriculture and Mining	42	2195	1.9
Manufacturing and Construction	30	599	5.0
Retail, Restaurants, and Hotels	35	1223	2.9
Services	40	1121	3.6
Info., Transport, Finance, and Others	10	333	3.0

Note: This table presents attrition statistics for our sample from the ENAHO-Panel covering 2018 to 2021. Baseline observations refer to workers who were employed in 2019. Attrited observations represent those who were not followed up in at least one of the years other than 2019. Attrition is disaggregated by our analytical groups of paralyzation and automation risk, as well as other socio-economic characteristics.

Table A.2: Essential and Paralyzed activities by economic sector

	N of private workers	Level of paralization				
Sector	2021	0	0.25	0.50	0.75	1.00
Agriculture and Fishing	352,446	93.1%	0.0%	6.0%	0.8%	0.0%
Mining	27,746	0.0%	0.0%	0.0%	5.2%	94.8%
Manufacture	428,173	52.4%	0.0%	8.2%	10.8%	28.7%
Commerce	592,380	26.3%	7.8%	10.4%	11.7%	43.8%
Non-personal Services	1,356,667	21.1%	3.7%	31.7%	20.4%	23.2%
Personal Services	231,727	1.1%	0.0%	0.0%	11.6%	87.3%
Households	26	0.0%	0.0%	0.0%	0.0%	100.0%
Unspecified	36,845	–	–	–	–	–

Note: This table displays the 2021 monthly average number of private formal workers in Peru by economic sector, and the percentage of those workers that belong to an ISIC four-digit level code classified by the employed paralization level. The level of paralization structure is built based on (MTPE, 2022)'s classification of industries as essential or (partially or totally) paralyzed. This classification is based on the activities described first on the March 15th 2020 decree (Decreto Supremo No. 044-2020-PCM) that enlisted the essential activities and was reviewed to follow closely the progressive reopening lined up by the next four phases of economic reactivation that took place between May and September 2020. Paralyzation categories are: 0 "essential", 0.25 "lightly paralyzed", 0.50 "partially paralyzed", 0.75 "strongly paralyzed", 1 "Fully paralyzed". Construction sector numbers are censored in the data due to a report issue. Source: Electronic Payroll from the Ministry of Labor and Promotion of Employment (MTPE). Last reviewed on January 13th, 2025: https://www.datosabiertos.gob.pe/dataset/n%C3%BAmero-de-trabajadores-del-sector-privado-por-meses-seg%C3%BAn-ciiu-clasificaci%C3%B3n-internacional-2.

Table A.3: 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	5471	2620	2851	2742	2729	644
Average labor income (PEN)	1427	1818	1068	881	1976	1190
Women	0.50	0.50	0.50	0.49	0.51	0.65
Men	0.50	0.50	0.50	0.51	0.49	0.35
Small and medium-sized firms	0.84	0.76	0.91	0.95	0.72	0.89
Large firms	0.16	0.24	0.09	0.05	0.28	0.11
Formal	0.23	0.35	0.13	0.05	0.42	0.13
Informal	0.77	0.65	0.87	0.95	0.58	0.87
Low-skilled	0.81	0.71	0.90	0.96	0.65	0.92
Medium-skilled	0.09	0.13	0.05	0.03	0.15	0.07
High-skilled	0.10	0.16	0.05	0.01	0.20	0.01
Agriculture and mining	0.40	0.04	0.73	0.76	0.04	0.03
Manufacturing and construction	0.11	0.18	0.04	0.04	0.18	0.17
Retail, restaurants and hotels	0.22	0.31	0.14	0.09	0.35	0.39
Services	0.20	0.37	0.06	0.09	0.32	0.37
Information, transport, finance and others	0.06	0.10	0.02	0.01	0.11	0.03

Note: This table presents descriptive statistics for the sample of individuals who were observed working in 2019 in the ENAHO panel aged 22 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.

Table A.4: Occupational composition of the high automation risk cells, 2019

ISCO	Occupation group	n	% of cell (n)	% of cell (weighted)
Panel A. Essential industries				
61	Skilled agricultural workers	1,244	59.29	58.26
92	Agricultural and fishery laborers	827	39.42	39.73
93	laborers in mining, construction and manufacturing	16	0.76	1.21
91	Cleaners and helpers	8	0.38	0.58
94	Food preparation assistants	2	0.10	0.21
63	Subsistence farmers	1	0.05	0.02
	Total	2,098	100.00	100.00
Panel B. Paralyzed industries				
91	Cleaners and helpers	243	37.73	41.14
93	laborers in mining, construction and manufacturing	152	23.60	20.78
95	Street sales and service workers	150	23.29	24.01
94	Food preparation assistants	92	14.29	13.62
92	Agricultural and fishery laborers	7	1.09	0.44
	Total	644	100.00	100.00

Note: ENAHO panel estimation sample, workers employed in 2019 and aged 22 to 70, tracked from 2018 to 2021. Panel A covers workers at high automation risk in essential industries; Panel B covers workers at high automation risk in paralyzed industries, the treated group. Occupation groups are two-digit ISCO-08, assigned from ENAHO's national occupational coding. Seven groups have a routinization task content index at or above the sample median of 0.778 and are therefore classified as at high automation risk; group 93 covers laborers in mining, construction, manufacturing and transport. Groups are ordered by size within each panel, and a group is omitted from a panel when no worker in that cell belongs to it. Weighted shares use the panel expansion factor. Agricultural occupations (61, 92 and 63) account for 98.7 percent of the essential high risk cell, and urban elementary occupations (91, 93, 95 and 94) for 98.9 percent of the treated cell.

Table A.5: Employment relationship by paralyzation status and automation risk, 2019

	Not a wage employee				Wage employee		
	Employer	Own account	Unpaid family	Total	Salaried employee	Manual worker	Domestic worker
Essential, low risk	2.1	48.9	5.4	56.4	34.1	9.3	0.0
Essential, high risk	3.4	55.9	25.1	84.5	0.2	15.2	0.0
Paralyzed, low risk	5.7	43.1	1.7	50.6	35.5	13.7	0.2
Paralyzed, high risk	0.5	37.6	4.0	42.1	3.6	36.2	18.2
All employed	3.7	48.2	11.5	63.4	18.0	16.3	2.2

Note: ENAHO panel estimation sample, workers employed in 2019 and aged 22 to 70, tracked from 2018 to 2021. Rows refer to the four combinations of paralyzation status and automation risk, with "low risk" and "high risk" abbreviating low and high automation risk. Cells are shares of workers in each row, unweighted, based on the employment relationship reported in ENAHO in 2019. Salaried employees and manual workers are separate categories in the survey and correspond broadly to white-collar and blue-collar wage employment. A residual category accounts for four workers in the sample and is omitted, so rows sum to slightly less than 100. The "Total" column groups employers, own account workers and unpaid family workers, none of whom is employed by another party under a wage relationship. Weighted shares are similar: 63.4 percent of workers are not wage employees unweighted and 53.6 percent weighted, with corresponding figures of 42.1 and 43.0 percent for the treated group.

Table A.6: Triple-difference model: Alternative Fixed Effects

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)
A. Employment							
Post * Paralyzed	-0.0322	-0.0303	-0.0311	-0.105***	-0.0273	-0.0283	-0.0322
	(0.0238)	(0.0235)	(0.0233)	(0.0318)	(0.0230)	(0.0233)	(0.0238)
Post * High Aut Risk	0.0506**	0.0513**	0.0510**	0.00712	0.0536**	0.0534**	0.0498**
	(0.0219)	(0.0215)	(0.0214)	(0.0269)	(0.0215)	(0.0218)	(0.0220)
Post * High Aut Risk	-0.122***	-0.123***	-0.122***	-0.0366	-0.131***	-0.130***	-0.121***
* Paralyzed	(0.0324)	(0.0321)	(0.0319)	(0.0367)	(0.0315)	(0.0320)	(0.0326)
Adjusted R^2	0.110	0.049	0.078	0.116	0.189	0.229	0.122
B. Labor Earnings							
Post * Paralyzed	-0.347**	-0.329*	-0.336**	-0.682***	-0.316*	-0.326*	-0.354**
	(0.168)	(0.169)	(0.164)	(0.248)	(0.164)	(0.167)	(0.168)
Post * High Aut Risk	0.621***	0.617***	0.625***	0.162	0.646***	0.645***	0.599***
	(0.209)	(0.210)	(0.203)	(0.220)	(0.198)	(0.202)	(0.207)
Post * High Aut Risk	-1.021***	-1.018***	-1.029***	-0.284	-1.023***	-1.017***	-0.993***
* Paralyzed	(0.260)	(0.259)	(0.253)	(0.293)	(0.251)	(0.257)	(0.259)
N	21719	21719	21719	21454	21719	21719	21719
Industry FE	X	-	X	-	-	-	X
Individual FE	-	-	-	-	X	X	-
Occupation FE	-	-	-	-	-	-	X
Quarter FE	X	-	-	-	-	X	X
Year X Industry FE	-	-	-	X	-	-	-

Note: This table displays the triple-difference coefficients resulting from estimating Equation 6 for the employment status dummy (Panel A) and the logarithm of labor earnings (Panel B) incorporating different schemes of fixed effects described in the bottom rows of the table. Clustered robust standard errors at the industry level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.7: Labor earnings effects: robustness to the treatment of zero earnings

	Baseline: log(w+1)	IHS(w)	log(w), employed only
Post * High Aut Risk	-1.021***	-1.126***	-0.101
* Paralyzed	(0.260)	(0.286)	(0.0766)
Adjusted R^2	0.140	0.133	0.289

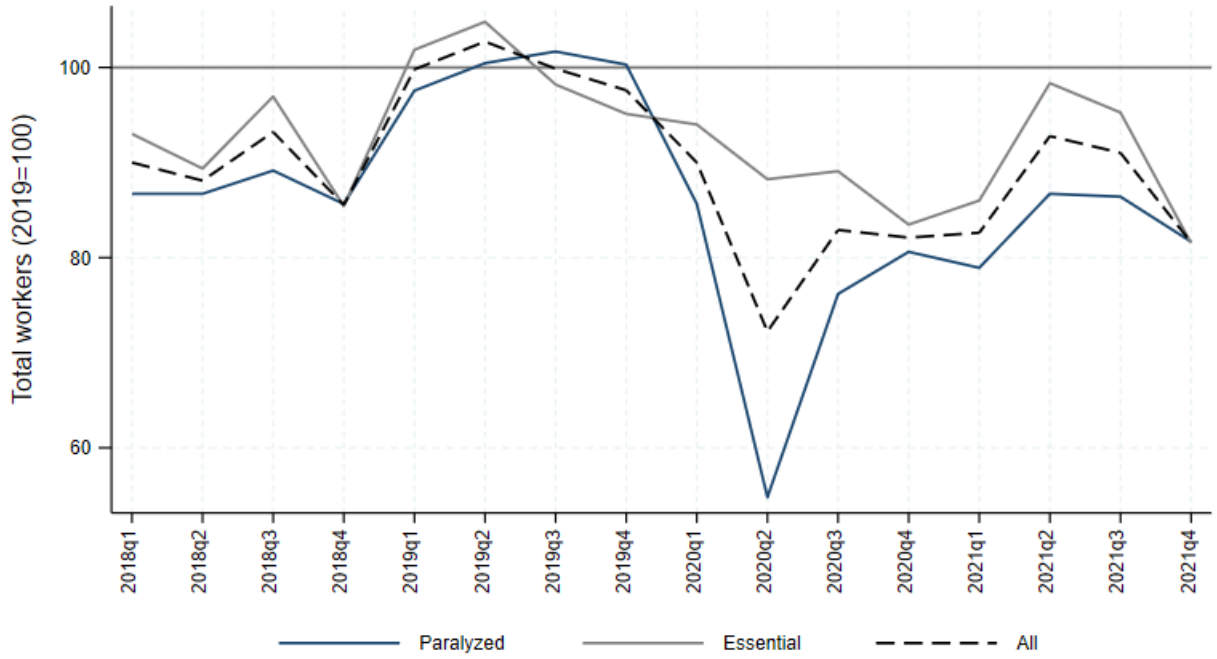
Note: This table reports the triple-difference coefficient on Post $\times$ High Automation Risk $\times$ Paralyzed from Equation 6 for the logarithm of labor earnings, under alternative treatments of workers with zero earnings. Column 1 reproduces the baseline labor-earnings specification (as in Table 3, Model 6), which assigns zero earnings to non-employed workers before taking logs, $\ln(w+1)$. Column 2 instead applies the inverse hyperbolic sine transformation to labor earnings, which also assigns zero to non-employed workers but is well-defined at zero without adding a constant before taking logs. Column 3 restricts the sample to workers who remain employed, dropping zero-earners entirely to isolate the intensive-margin earnings effect. All columns include industry and quarter fixed effects. Clustered robust standard errors at the industry level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.8: Triple-difference model: Alternative specifications

	Baseline	Continuous	Alt. RTI	FO estimates	Excl. unpaid family	Interacted FE	More telework	Less telework
A. Employment								
Post * Paralyzed	-0.0322	-0.0983***	-0.0514**	-0.0852***	-0.0266	-0.105***	-0.0340	0.122
	(0.0238)	(0.0218)	(0.0243)	(0.0219)	(0.0278)	(0.0318)	(0.0247)	(0.171)
Post * High Aut Risk	0.0506**	0.00944	0.0365*	-0.0525***	0.0569**	0.00712	0.107*	0.194
	(0.0219)	(0.00967)	(0.0203)	(0.00962)	(0.0278)	(0.0269)	(0.0639)	(0.171)
Post * High Aut Risk	-0.122***	-0.0448***	-0.0708**	-0.00664	-0.137***	-0.0366	-0.220***	-0.268
* Paralyzed	(0.0324)	(0.0139)	(0.0320)	(0.0213)	(0.0355)	(0.0367)	(0.0694)	(0.173)
Adjusted R^2	0.110	0.110	0.109	0.114	0.132	0.116	0.119	0.109
B. Labor Earnings								
Post * Paralyzed	-0.347**	-0.899***	-0.462***	-0.649***	-0.298*	-0.682***	-0.359**	0.380
	(0.168)	(0.156)	(0.151)	(0.149)	(0.180)	(0.248)	(0.175)	(0.955)
Post * High Aut Risk	0.621***	0.249	0.503**	0.165	0.382**	0.162	0.432	1.235
	(0.209)	(0.157)	(0.209)	(0.300)	(0.184)	(0.220)	(0.380)	(0.974)
Post * High Aut Risk	-1.021***	-0.456***	-0.763***	-0.487	-0.852***	-0.284	-0.612	-1.776*
* Paralyzed	(0.260)	(0.171)	(0.258)	(0.329)	(0.223)	(0.293)	(0.395)	(0.993)
N	21719	21719	21719	21719	19221	21454	10750	10969
Industry FE	X	X	X	X	X	-	X	X
Quarter FE	X	X	X	X	X	-	X	X
Year X Industry FE	-	-	-	-	-	X	-	-

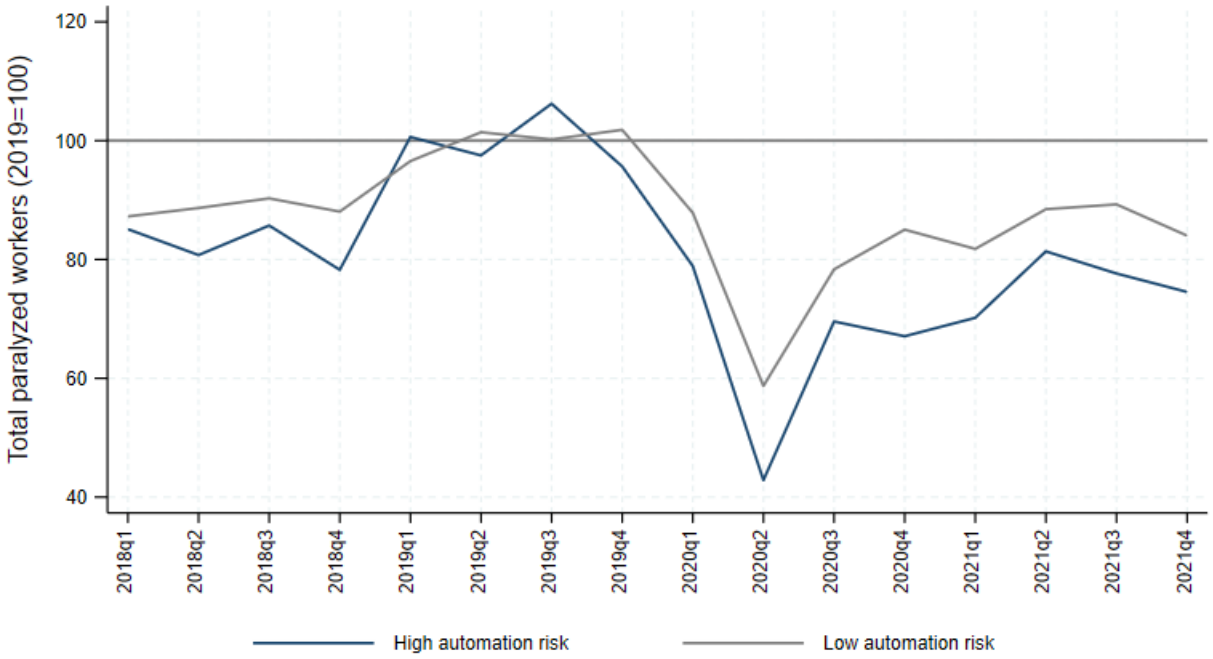
Note: This table displays the triple-difference coefficients resulting from estimating Equation 6 for the employment status dummy (Panel A) and the logarithm of labor earnings (Panel B) under different specifications. The first column presents the baseline scenario (similar to Table 3). The second column uses the continuous automation risk variable (standardized) instead of the binary transformation. The third column uses an alternative definition of RTI following Gasparini *et al.* (2021), with two additional conditions: not calculating budgets or costs, and not giving presentations. The fourth column employs Frey and Osborne (2017) (FO) estimates of automation risk instead of RTI estimates. The fifth column excludes workers who in 2019 were unpaid family workers, and recodes as non-employed any worker who is observed as an unpaid family worker in any other year. The sixth column includes interacted year-industry fixed effects; we estimated these high-dimensional fixed effects following Correia *et al.* (2016). The last two columns display the estimations for jobs that are both more and less eligible for remote work, respectively. Clustered robust standard errors at the industry level are in parentheses. $*p < 0.10, **p < 0.05, ***p < 0.01$

Figure A.1: Evolution of paralyzed and essential jobs in Peru, 2018–21



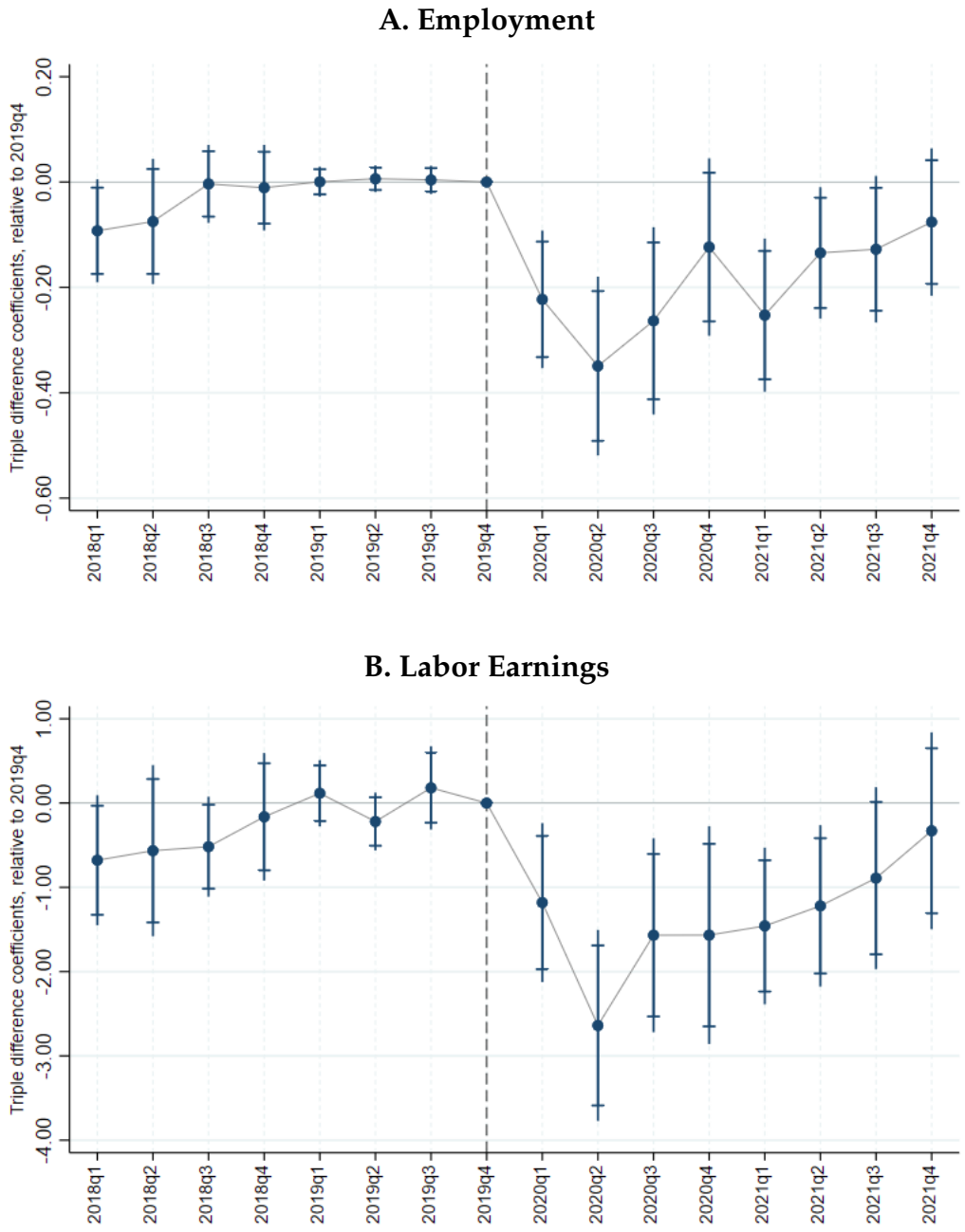
Note: This figure displays the evolution of employment in Peru for industries that were ex post categorized as either essential or paralyzed because of pandemic-related restrictions. Data are from the ENAHO panel and use the same estimation sample and treatment definitions as the main results (Section 5).

Figure A.2: Evolution of paralyzed jobs in Peru by automation risk, 2018–21



Note: This figure displays the evolution of paralyzed jobs in Peru, categorized by automation risk. High-risk jobs include those with a routinization-task-content index at or above the sample median. Data are from the ENAHO panel and use the same estimation sample and treatment definitions as the main results (Section 5).

Figure A.3: Effect of mobility restrictions and automation risk on the labor market (ignoring occupational mobility from low- to high-risk occupations): Dynamic triple-difference model, 2018–21



Note: The figure shows quarterly point estimates, along with the 90% and 95% confidence intervals of the dynamic triple-difference model described in Equation 7 for the employment-status dummy (Panel A) and the logarithm of labor earnings (Panel B) using data from 2018 to 2021 and not including workers that moved from low- to high-risk jobs after 2020: in Panel A, these workers are recoded as not employed in the quarters after the switch; in Panel B, they are dropped from the sample in the quarters after the switch. High automation risk is defined as workers with a routinization-task-content index at or above the sample median. Standard errors are clustered at the industry level.