Science and Public Policy, 2023, **50**, 565–578
DOI: https://doi.org/10.1093/scipol/scad007
Advance Access Publication Date: 23 March 2023
Article

OXFORD

Are we nearly there yet? New technology adoption and labor demand in Peru

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Abstract

Forecasts about the effects of new technologies on labor demand are generally pessimistic. However, little is known about the current level of technology adoption and its effect on labor demand, particularly in developing countries. This paper exploits a national representative employer survey and administrative data from Peru to offer empirical evidence in this regard. Our results show that the adoption of new technologies by firms is still incipient in the country. However, when adopted, they slightly reduce the demand for workers in the medium term, particularly those in high-skilled and non-routine occupations, with a temporary job contract, and during the COVID-19 pandemic.

Key words: automation; labor demand; employer survey; employer–employee data.

1. Introduction

The use of new technologies, such as artificial intelligence (AI) and robotics, is increasing at a rapid pace as their prices fall (Nordhaus 2007; Graetz and Michaels 2018). Although this has been the case for a number of years, the Coronavirus disease (COVID-19) pandemic seems to have accelerated this trend worldwide (World Economic Forum 2020). Forecasts of the effects of these new technologies on labor demand are divergent but are mostly pessimistic (Pew Research Center 2017). This is particularly true for developing countries, where about two out of three jobs are expected to experience significant automation (World Bank 2016). However, evidence about the current effect of new technology adoption on labor demand is still scarce, in part due to a lack of specific firm-level data about the use of these technologies (Seamans and Raj 2018). Using a national representative employer survey in Peru, the Encuesta Nacional de Habilidades al Trabajo (ENHAT) (Novella et al. 2019),[1] and administrative records of formal firms and workers, this paper offers empirical evidence about the adoption level of new technologies and its effects on the labor demand in a developing country.

Studying the degree of adoption of these technologies and its effect on labor demand in the context of developing countries is important for several reasons. First, it allows a better understanding of the constraints that firms face in improving their productivity and competitiveness in both local and global markets. Second, it enables the identification of the groups of workers and firms who are more likely to suffer from the widespread adoption of new technologies. Finally, it provides useful information for the design of public policy interventions aimed at improving countries' technology adoption process, growth, and development.

Recent empirical studies about the effect of technology adoption on labor demand in developed countries show mixed results. While some estimate that around 47 per cent of employment in the USA is at risk of automation (Frey and Osborne 2017), others indicate that only 14 per cent of jobs are at high risk of automation across the Organisation for Economic Co-operation and Development (OECD 2019). However, evidence on the impact of technological progress on labor demand in developed countries (Goos and Manning 2007; Autor et al. 2006; Goos et al. 2014) can hardly be extrapolated to developing countries because, among other reasons, the latter usually face a lower presence of information and communication technology (ICT), higher ICT prices, and differences in industrial composition (Maloney and Molina 2016; Eden and Gaggl 2015). Estimates for developing countries are, in general, worrisome. For instance, in Uruguay and Argentina, it is estimated that 66 and 64 per cent of the workforce, respectively, would be replaced by automation technologies (Aboal and Zunino 2017).

Peru offers an interesting setting for studying the effect of new technology adoption on labor demand. Although there have been significant improvements in growth and poverty reduction, the country still faces important challenges related to poor productivity, high informality, and low human capital development (Fernández-Arias 2014; Busso et al. 2017). These challenges were accentuated by COVID-19; in the first year of the pandemic, relative to 2019, the gross domestic product shrunk 11 per cent, the employment rate reduced by 15 per cent, and the poverty rate increased by 10 percentage points. The country also suffers from low levels of human capital, which explains why almost half of the firms in Peru struggle to fill in their vacancies (Novella et al. 2019). Using the ENHAT, the authors descriptively show that the main reasons behind this are a lack of job experience and skills among jobseekers.

Although the degree of technology adoption and innovation in Peru is comparable to the average performance of Latin American and developing countries,[2] Peru appears to be particularly susceptible to the adoption of new technologies. Using occupation-level data, Chui et al. (2017) estimated that 53 per cent of all work activities in the country are at risk of automation, which was the highest figure among the five South American countries that were part of the study. This high level of vulnerability is reiterated by Brambilla et al. (2018), who use task-level data and show that Peru has a higher risk of employment automation than the Latin American average.

In this paper, we use an instrumental variable (IV) approach to identify the effect of new technology adoption on labor demand. We do so by using, as the IV, the change in the number of internet satellite antennas in the municipality where the firm is located (between 2007 and 2012). Our outcomes of interest are the overall employment growth rate, the growth rate by skills level, major occupational groups, and type of job contract. We also analyze our results by task routineness and across the wage distribution.

We combine information from an enterprise survey and an administrative dataset for formal firms and employees in Peru. The first dataset we use is the ENHAT—a firm-level survey conducted between 2017 and 2018. The ENHAT was designed by the Inter-American Development Bank (IDB) to measure skills gaps in the country and gather information about the strategies adopted by firms to deal with such gaps, including the adoption of new technologies. Second, we use the Peruvian administrative payroll data (named Planilla Electrónica [PE]), which contain rich monthly employer–employee information. The PE dataset used in this paper includes monthly records of all formal workers and firms in Peru between 2011 and 2020. Combining both datasets allows us to study the effect of adopting new technologies before 2017/2018 on mid-term employment growth until December 2020, that is including periods when the COVID-19 pandemic hit the country's economy the hardest (second and third trimester of 2020) and the start of the recovery phase (fourth trimester of 2020).

We find that only 29 per cent of formal firms in Peru had adopted new technologies in 2017/2018, a proportion that shrinks to 9 per cent when advanced network services are not considered. On average, these firms are larger and older than non-adopting firms. Furthermore, we find that the use of new technologies slightly reduces the labor demand for workers in the medium term (i.e. around 2 years after observing the technology adoption). This is particularly true for those in high-skilled/non-routine cognitive occupations, professionals and technicians, those with a temporary job contract, and those in the middle-upper part of the wage distribution. Similar results are found when separately analyzing the effects of different types of technologies, such as advanced network services and AI.

The still incipient use of new technologies among Peruvian firms and its reduced effect on labor demand might change in the future. For instance, even before the start of the COVID-19 pandemic, we find that 35 per cent of firms in the country expected to adopt new technologies in the next 3 years. Before the adoption of new technologies becomes ubiquitous, developing countries, such as Peru, have the chance to strengthen their investment in human capital and provide their workers with the skills and learning capacities to reduce the likelihood of being displaced by automation in a changing labor market.

The rest of the paper is organized as follows: Section 2 discusses how technology use is related to labor demand; Section 3 presents the data; Section 4 describes the methodology of analysis; Section 5 presents the results; and, finally, Section 6 presents the conclusions.

2. New technology and labor demand

Technological change might affect labor demand through three main channels (Gregory et al. 2016). First, it might reduce labor demand through a substitution effect, whereby reductions in the cost of capital lead firms in the high-tech tradable sector to substitute labor inputs for capital. Second, technological change might increase labor demand through a product demand effect, as reductions in the cost of capital (and consequently in the price of tradables) may lead to growth in product and labor demand. Third, product demand spillovers may create additional labor demand: the increase in product demand raises income, which is partially spent on low-tech non-tradables, leading to higher local labor demand.[3] The aggregated effect of technological innovation on employment would thus vary with the type of innovation (i.e. process or product), the associated displacement (e.g. process innovations reducing employment), and compensation effects (i.e. related to changes in the demand for products) (Harrison et al. 2014).

The recent literature about the effect of new technology adoption on labor demand has moved from the 'canonical model' to a task-based approach. The former emphasizes that the effect of technological change depends on workers' skills level (Autor et al. 1998, 2008; Carneiro and Lee 2011). However, this approach fails to explain several stylized facts, such as job polarization (Acemoglu and Autor 2011), the substitution of workers in certain tasks (Autor et al. 2003; Cortes and Salvatori 2019), and offshorability (Blinder and Krueger 2013).[4] The task-based approach, developed by Acemoglu and Restrepo (2019), intends to overcome these deficiencies. The authors model the displacement effect of automation as the effect on tasks that were previously performed by workers. The model predicts that while a displacement effect reduces labor demand and wages, the use of automation reduces production costs and increases productivity, which increases the demand for labor in non-automated tasks. Moreover, sectors and occupations not directly affected by the technological change might expand after absorbing workers freed from sectors and occupations affected by the technological change. Finally, the authors show that productivity improvements due to new technology might even expand employment in affected industries (Acemoglu and Restrepo 2018a, 2018b).

The effect of new technologies on labor demand would not affect all tasks and occupations homogeneously. Autor et al. (2003) argue that technological change might disproportionately affect jobs involving routine tasks. Declines in the cost of using ICT and the productivity improvements associated with it might lead firms to substitute workers performing routine or codifiable tasks with new technology. In particular, this could be the case for some of the tasks of middle-skilled workers (e.g. production and administrative manual tasks) (Michaels et al. 2014). In contrast, new technologies might not affect the two extremes of the skills distribution. On the one hand, new technologies are expected to be a complement, rather than a substitute, for high-skilled or managerial, professional, technical, and creative occupations. On the other hand, new technologies would not affect non-routine manual tasks and services occupations because their adaptability and responsiveness to unscripted interactions would exceed the capacity of technology or be relatively too expensive to be computerized (Acemoglu and Autor 2011; Autor and Dorn 2013).

However, the nature of tasks that are automatable is constantly being challenged by the advances of new technologies. Brynjolfsson and McAfee (2012) argue that new technologies might replace humans in tasks beyond routine manual ones. As an example, they mention that driving a car was considered a non-manual routine task and is now fully automatized by autonomous transport technology. In this context, Frey and Osborne (2017) expand and update the routine-task framework of Autor et al. (2003) in order to include recent technologies, particularly AI and machine learning (ML), and allow computer capital to substitute labor across a wide range of non-routine tasks. Based on the Occupational Information Network (O*NET), an online database containing the most complete set of occupational definitions of the USA, they estimate the probability of computerization of 702 occupations.[5] They estimate that around 10 per cent of the occupations are already fully computerizable.

Empirical evidence about both the current level of new technology adoption and its effect on labor demand is scarce. The available research mainly focuses on the effect of ICT. Akerman et al. (2015) find that broadband adoption by Norwegian firms increases the wages of skilled workers, mainly by performing non-routine abstract tasks and substituting low-skilled workers in routine manual tasks. Using a proxy of technological exposure, Montresor (2019) finds that while technological change has substituted for routine labor in the UK, it has not affected non-routine skilled employment. Weinberg (2000) finds that the adoption of computers increases the labor demand for female workers in the USA, and Gaggl and Wright (2017) find that ICT investment at the firm level increases employment and earnings of non-routine cognitive workers in Norway but decreases employment and earnings of routine cognitive workers (no effect is found on manual workers). Using firm-level data from Finland, Böckerman et al. (2019) find that the use of ICT is positively associated with the demand for high-skilled and abstract workers and negatively associated with the demand for low-skilled or routine workers. However, evidence on other automation technologies, such as programmable controllers, computer-automated design, and numerically-controlled machines, finds no marked effect on wages and employment in manufacturing firms in the USA (Doms et al. 1997).

Evidence regarding the effect of AI or automation technologies is incipient. Bessen et al. (2020) analyze the impact of automation investments on employment and wages in the Netherlands, finding that firms that experienced automation events have higher employment growth than not-automating firms. However, employment growth among the former group slows down after the automation events when compared to previous periods. In contrast, daily wages rise in the succeeding years after the automation investment. Acemoglu et al. (2022) use vacancy-level data to investigate the effect of AI technology on the US labor market. They find that firms that have an occupational structure compatible with current AI capabilities (in 2010) reduce their vacancies for non-AI positions. When analyzing at the industry or occupational level, the authors do not find any significant effects.

The evidence for developing countries is scarcer, and its results are equivocal. On the one hand, investments in ICT in Argentina have increased the demand for both low- and high-skilled workers but particularly for the latter group (Brambilla and Tortarolo 2018). In Mexico, internet use has increased the demand for skilled workers relative to unskilled workers, but the wage gap between the two has decreased (Iacovone and Pereira-Lopez 2017). Internet availability in Brazil did not affect overall employment but did affect the demand for low-skilled workers by replacing routine tasks (Almeida et al. 2017b; Dutz et al. 2017). Similarly, internet adoption in Peru increased the demand for production workers with permanent contracts and decreased the demand for administrative workers with temporary contracts and non-remunerated workers (Viollaz 2018). On the other hand, in Chile, the adoption of complex software increased the share of administrative and unskilled production workers and reduced the share of skilled production workers (Almeida et al. 2017a). Moreover, Crespi and Tacsir (2013) show the evidence of skill-biased product innovation in a sample of four Latin American countries (Argentina, Chile, Costa Rica, and Uruguay). Cirera and Sabetti (2019), in turn, show larger effects of innovations on total employment in low-income countries than in middle- and high-income countries.

Compared to the well-established evidence on job polarization in developed countries (Autor et al. 2006; Goos and Manning 2007), results from developing countries are mixed. Mexico and Brazil show signs of skill-biased technical change (SBTC), while Peru and Chile show reduced signs of job polarization through the substitution of middle-skilled or routine workers. These results align with the view that there is no evidence of job polarization in developing countries, except for Chile, where the stage of the technological progress might be more advanced than in other less-developed countries and Latin American countries (Maloney and Molina 2016). On the contrary, the changes in the occupational structure in Latin American countries are more consistent with the SBTC framework (Messina and Silva 2017).

Moreover, in part due to limitations of information about new technology use, the vast majority of recent literature on the effect of these technologies on labor demand has relied on indirect proxies of automation, such as routine task input (Autor et al. 1998, 2008, 2003; Goos and Manning 2007; Autor and Dorn 2013; Autor et al. 2015), investment in computer capital (Beaudry et al. 2010; Michaels et al. 2014), investment in robots (Acemoglu and Restrepo 2020; Graetz and Michaels 2018; Acemoglu et al. 2020), patent grant texts (Mann and Püttmann 2021), and AI-related vacancies (Acemoglu et al. 2022). However, these proxies all have shortcomings in measuring automation comprehensively. For instance, data about investment in robots might introduce several biases due to inaccuracies in the definition of robots and poor industry and geographic classifications

(Seamans and Raj 2018). Also, patent grant text classification is an inherently-imprecise activity and might introduce further inaccuracies through probabilistic matching of patents to industries and commuting zones (Mann and Püttmann 2021). The data used in this paper allow us to directly identify the use of new technologies by firms.

3. Data and sample characteristics

3.1 Survey and administrative data

In this paper, we combine information from an enterprise survey and an administrative dataset for formal firms and employees in Peru. Our first dataset, ENHAT, is an employer survey conducted in Peru from September 2017 to March 2018. The ENHAT is statistically representative at the national, firm-size, and sectoral levels for private formal firms. The ENHAT was designed by the IDB, and the data were collected by the National Institute of Statistics and Informatics (INEI). It aims at measuring the skills gap, identifying its causes and consequences from the firms' perspectives, and understanding the strategies adopted by firms to overcome it. A distinctive feature of the ENHAT is that it contains detailed information about the adoption of new technologies.

The sample size of the ENHAT was 4,105 small, medium, and large formal firms operating in almost all sectors (excluding agricultural and public sectors) in Peru.[6] Considering that 86 per cent of the (4,105) sample answered the survey, some firms have missing information in key variables. Furthermore, due to our empirical strategy (explained in Section 4), the final sample size for this study corresponds to 2,056 firms.[7] The sample is probabilistic, stratified, and independent in each of the sections of the International Standard Industrial Classification Revision 4. Firm size is defined by net annual sales in three categories: small firms (87 per cent), with sales between USD 175,445 and USD 1,988,377; medium-sized firms (3 per cent), with sales between USD 1,988,377 and USD 2,690,158; and large firms (10 per cent), with sales above USD 2,690,158.[8]

We merge the ENHAT with the PE data[9] to obtain a rich employer–employee dataset with monthly information. The PE dataset used in this paper includes monthly records of all formal workers and firms in Peru between January 2011 and December 2020. The two datasets are combined using the unique firm fiscal ID number.[10] Across all months, there are 2 per cent of missing observations on average, and the highest number was in May 2020, with 10 per cent. This was because some firms exited the market.

The major occupational groups (at one digit) in the PE administrative dataset are equivalent to the ones of the International Standard Classification of Occupations 1988. We reclassified the information of occupations into low-, middle-, and high-skilled occupations. High-skilled occupations include managers, professionals, and technicians; middle-skilled occupations include clerical support workers; and low-skilled occupations include jobs in personal services, sales, agricultural, forestry, fishery, craft, related trades occupations, plant and machine operators, assemblers, and elementary occupations.

Moreover, in contrast to the available evidence, by using the ENHAT, we are able to directly identify the use of new technologies by firms. In the ENHAT, the information about the use of automation technologies was collected using the following question: 'Does the firm currently use any of the following technologies for producing goods or services?' The list of technologies comprises the six technologies most commonly mentioned in the recent literature about trends of automation jobs and new technologies: AI (Acemoglu and Restrepo 2018b), advanced robotics (Graetz and Michaels 2018), autonomous transport (Gittleman and Monaco 2020), advanced manufacturing (Gómez and Vargas 2012), 3D printing (Beltagui et al. 2020), and advanced network services (DeStefano et al. 2020).

These technologies may affect employment differently. AI involves technology that is able to perceive its environment and learn and carry out tasks intelligently. Examples of this technology are ML, natural language processing, and image or speech recognition. Advanced robotics uses robots to carry out complex automated tasks (e.g. robotic surgery or automated storage system). Autonomous transport implies the use of unmanned vehicles such as drones or any driverless car. 3D printing and advanced manufacturing are similar because they involve manufacturing processes. Examples of advanced manufacturing production are rapid prototyping or microfabrication. These technologies are commonly used with 3D printing technology, which is a technology that constructs three-dimensional objects based on digital models. Finally, advanced network services are mainly associated with information technology occupations. Cloud computing, big data, and the internet of things are examples of advanced network services.

Unfortunately, the ENHAT does not allow us to exactly identify the date when firms adopted a particular technology. Instead, we know whether, at the time of the interview, firms use (or do not use) new technologies. In the paper, we estimate the effects of technology adoption relative to the time of the interview, as if this were the time when firms adopted new technologies. In particular, we define short-time effects as those happening after 12 months and medium-term effects as those happening after 24 months of the date when firms were surveyed.

3.2 Sample characteristics

We now turn to show the main characteristics of firms in the sample, focusing primarily on describing the differences between firms adopting and not adopting new technologies. Table 1 shows that the use of these new technologies among firms in Peru in 2017–8 is still incipient, except for advanced network services. On average, only 29 per cent of firms use at least one of these technologies, and this proportion shrinks to 9 per cent when advanced network services are not considered. Regarding employment outcomes, Table 1 shows that overall employment decreased by 6 per cent, on average, in the 2-year period after ENHAT data were collected, which possibly reflects the discussed effect of COVID-19 on the employment rate. Although firms using at least one new technology seem to have a lower percentage change of employment than non-adopting firms, the difference is not statistically significant. Likewise, changes in employment appear larger for high- and low-skilled workers rather than for the middle-skilled, although, again, the difference is not statistically significant.

Regarding the firm's characteristics associated with the adoption of new technologies, Table 2 shows that the firm size, measured by the number of employees, is positively associated

Table 1. Descriptive statistics of the sample.

Variable	All Mean	All (SE)	Not using technologies Mean	Not using technologies (SE)	Using technologies Mean	Using technologies (SE)	Sig. mean test
Use of new technologies in 2017–8							
AI	0.04	(0.005)	0.00	(0.000)	0.14	(0.016)	***
Advanced robotics	0.01	(0.002)	0.00	(0.000)	0.02	(0.006)	***
Autonomous transport	0.01	(0.002)	0.00	(0.000)	0.02	(0.007)	***
Advanced manufacturing	0.03	(0.004)	0.00	(0.000)	0.11	(0.015)	***
3D printing	0.02	(0.003)	0.00	(0.000)	0.06	(0.011)	***
Advanced network services	0.25	(0.011)	0.00	(0.000)	0.86	(0.017)	***
At least one technology	0.29	(0.012)	0.00	(0.000)	1.00	(1.000)	
Employment growth 24 months after the ENHAT interview							
Total labor	−0.06	(0.014)	−0.06	(0.017)	−0.04	(0.024)	
High-skilled labor	−0.06	(0.018)	−0.05	(0.022)	−0.08	(0.028)	
Middle-skilled labor	−0.03	(0.028)	−0.05	(0.035)	0.01	(0.043)	
Low-skilled labor	−0.06	(0.030)	−0.05	(0.036)	−0.08	(0.054)	
Manager	−0.10	(0.025)	−0.07	(0.032)	−0.16	(0.041)	*
Professional	−0.01	(0.035)	−0.03	(0.046)	0.03	(0.053)	
Technician	−0.12	(0.032)	−0.13	(0.042)	−0.12	(0.047)	
Administrative worker	−0.03	(0.028)	−0.05	(0.035)	0.01	(0.043)	
Service and sales worker	−0.02	(0.058)	−0.03	(0.068)	−0.01	(0.115)	
Agricultural worker	0.19	(0.237)	0.25	(0.424)	0.12	(0.166)	
Craft and construction worker	0.10	(0.062)	0.07	(0.076)	0.15	(0.106)	
Plant and machine operator	−0.09	(0.051)	−0.07	(0.065)	−0.13	(0.082)	
Elementary occupations	−0.09	(0.039)	−0.09	(0.050)	−0.09	(0.058)	
Level of routineness							
Non-routine cognitive labor	−0.06	(0.018)	−0.05	(0.022)	−0.08	(0.028)	
Routine manual labor	−0.05	(0.043)	−0.05	(0.052)	−0.06	(0.075)	
Non-routine manual labor	−0.09	(0.038)	−0.08	(0.049)	−0.12	(0.056)	
Routine cognitive labor	−0.05	(0.026)	−0.08	(0.031)	0.02	(0.043)	*
Type of contract							
Permanent	−0.10	(0.016)	−0.11	(0.020)	−0.07	(0.026)	
Temporary	0.06	(0.029)	0.06	(0.036)	0.06	(0.050)	
Observations	2,056		1,338		718		

Source: ENHAT 2017–8 and PE.
Notes: Calculations use ENHAT sample weights. Employment growth refers to the percentage change of employment 24 months after the time of the survey interview. Standard errors (SEs) are in parenthesis. Significance for mean tests between firms not using and using new technologies: * significant at 10%, ** significant at 5%, and *** significant at 1%.

with technology adoption. Firms using new technologies have approximately forty more workers at the time of the interview (and 6 years before then) than non-technology-user firms.

Firms have been operating, on average, for 16 years, with those adopting new technologies being slightly older. Relative to firms not using new technologies, adopting firms belong to specific economic sectors, such as information and communication, professional and scientific, and education.

4. Empirical strategy

We rely on the exogeneity of broadband availability years before the technology adoption to identify the causal effect of new technology adoption on labor demand. Our identification strategy follows Akerman et al. (2015) in using municipality-level information on the availability of broadband internet as an IV. Thus, we estimate the following two-stage least-squared regression:

$$Tech_{i0} = Z_i\alpha + \delta Controls_{i0} + \varepsilon_{i0} \quad (1)$$

$$Growth_{it} = \widehat{Tech}_{i0}\beta + \theta Controls_{i0} + \mu_{i0} \quad (2)$$

where $Growth_{it} = \frac{Labor_{it} - Labor_{i0}}{(Labor_{it}+Labor_{i0})0.5}$, which is a standard definition for the growth rate of employment (Davis et al. 1998; Chodorow-Reich 2014). $Labor_{it}$ is the employment outcome of firm i observed at month t. $Labor_{i0}$ is the employment level at Month 0, which is the month when the ENHAT data were collected. The dependent variable in measures the percentage change of employment with respect to late 2017 and early 2018. $Tech_{i0}$ is a dummy variable that takes the value of 1 if firm i uses such a technology, and $Controls_{i0}$ are a set of control variables, both observed at Month 0. We use the change in the number of internet satellite parabolic antennas between 2007 and 2012 in each municipality as the instrument (Z_i). This information, collected at the district level (INEI 2020), was merged to the ENHAT using the district unique ID contained in both datasets.

We argue that the change in the number of parabolic antennas providing access to the high-speed internet through satellite communication is a relevant and valid instrument. As shown in Fig. 1, there was an increase in internet access through parabolic antennas during the 2007–12 period. Moreover, the fact that, before 2012, more than 50 per cent of the parabolic antennas were for commercial purposes and none were for residential use (Osiptel 2019) supports the argument that our IV is mainly relevant for firms rather than

Table 2. Descriptive statistics of the control variables.

Variable	All Mean	All (SE)	Not using technologies Mean	Not using technologies (SE)	Using technologies Mean	Using technologies (SE)	Sig. mean test
Control variables							
Number of workers (thousands)	0.05	(0.006)	0.04	(0.006)	0.08	(0.011)	***
Number of workers in 2011 (thousands)	0.04	(0.005)	0.03	(0.005)	0.07	(0.012)	***
Firm age	16.22	(0.266)	15.78	(0.316)	17.31	(0.489)	***
Years in the current location	12.78	−0.262	12.94	(0.314)	12.38	(0.474)	
Located in a large city	0.66	(0.013)	0.65	(0.016)	0.70	(0.022)	**
Economic sectors							
Manufacturing	0.12	(0.008)	0.12	(0.009)	0.14	(0.014)	
Construction	0.06	(0.007)	0.06	(0.008)	0.06	(0.012)	
Trade	0.39	(0.014)	0.42	(0.017)	0.31	(0.024)	***
Transportation	0.11	(0.007)	0.12	(0.009)	0.10	(0.012)	
Hotel and tourism	0.04	(0.005)	0.04	(0.006)	0.03	(0.007)	
Information and communication	0.02	(0.003)	0.01	(0.003)	0.04	(0.008)	***
Financial and insurance	0.01	(0.001)	0.01	(0.001)	0.02	(0.003)	***
Real estate	0.02	(0.002)	0.02	(0.003)	0.01	(0.003)	*
Professional and scientific	0.06	(0.006)	0.04	(0.006)	0.10	(0.015)	***
Administrative and support	0.06	(0.007)	0.06	(0.008)	0.06	(0.012)	
Education	0.03	(0.003)	0.02	(0.003)	0.04	(0.007)	***
Health	0.02	(0.003)	0.02	(0.003)	0.03	(0.006)	*
Arts and entertainment	0.01	(0.002)	0.01	(0.002)	0.01	(0.003)	
Other services	0.04	(0.005)	0.04	(0.006)	0.03	(0.007)	
Natural resources	0.02	(0.002)	0.02	(0.003)	0.02	(0.005)	*
Observations	2,056		1,338		718		

Source: ENHAT 2017–8 and PE.
Notes: Calculations use ENHAT sample weights. Standard errors (SEs) are in parenthesis. Significance for mean tests between firms not using and using new technologies: * significant at 10%, ** significant at 5%, and *** significant at 1%.

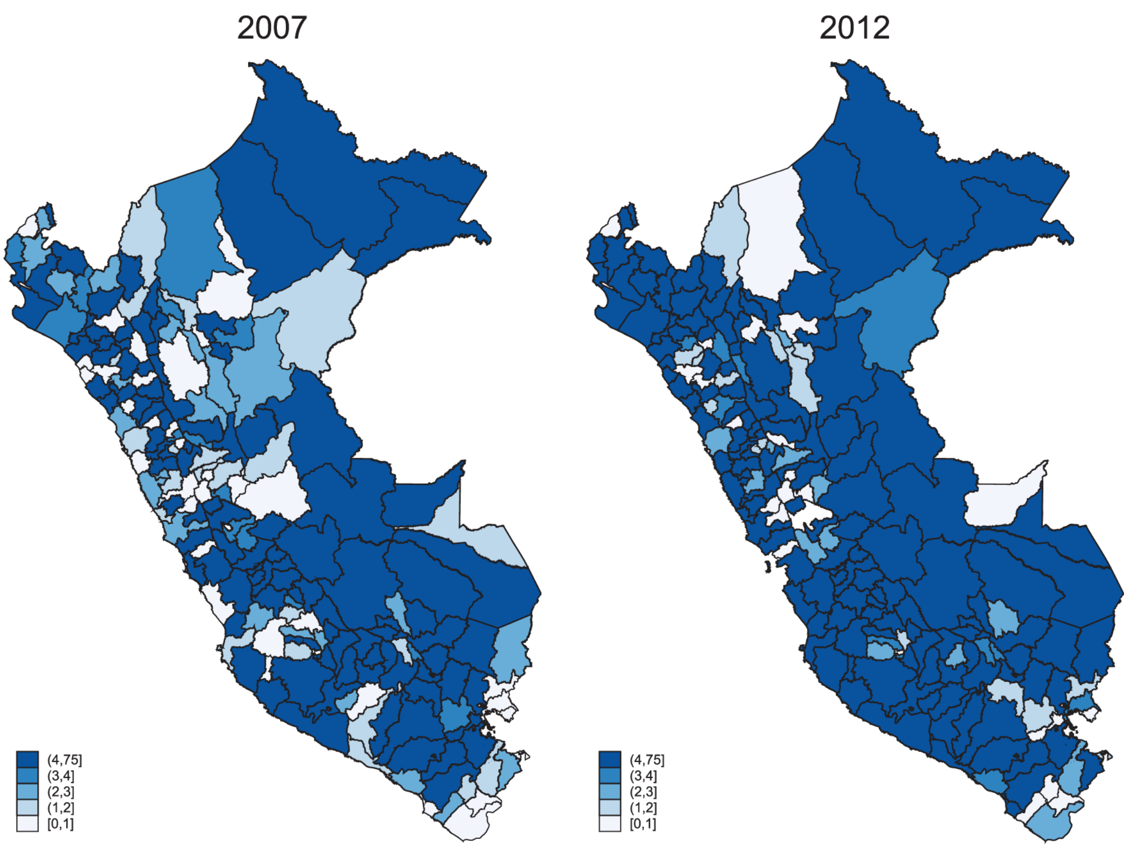

Figure 1. The number of internet satellite parabolic antennas in 2007 and 2012 by provinces (source: INEI (2020)).

for households.[11] Furthermore, we focus on the 2007–12 period because internet access was still not widely available in Peru during this time, and AI was not widely used either. Thus, we argue that the change in the number of internet satellite parabolic antennas from 2007 to 2012 provides a plausible exogenous variation that is strictly related to the adoption of new technologies at the firm level and only affects employment outcomes through technology adoption.[12]

We use a number of control variables affecting the technology adoption. To control for experience in the market, we include firms' years of operation (Coad et al. 2016). In addition, we include the number of years that the firm has been in the current location to account for migration patterns of firms that might move to locations where better infrastructure for technology is available. Because technological infrastructure might be better off in modern locations, we include a dummy variable to account for being located at the country's largest city (Lima). We use the number of workers 6 years before the interview and the number of workers at the moment of the interview to account for the firm size. All regressions include one-digit sector fixed effects to account for the plausible different uses of new technologies across economic sectors. Lastly, we use dummy variables for the month in which ENHAT data were collected for each firm.

We define four sets of dependent variables to explore how new technology adoption might affect labor demand. First, we estimate the effect on the overall employment growth of the firm. Second, we estimate the effect on the growth rate of high-, middle-, and low-skilled workers, separately. Third, we estimate the effect on the employment growth of routine jobs. Using the definition by Acemoglu and Autor (2011), we classify jobs according to the prevailing routine level of their tasks: non-routine cognitive (managers, professionals, and technicians)[13], routine cognitive (clerical support workers and sales workers), non-routine manual (care workers, personal services workers, and elementary occupations), and routine manual (craft and related trades workers, plant and machine operators, and assemblers).[14] Moreover, we examine the impact of technology adoption on each major occupational group. Finally, we explore the effect of technology adoption on permanent and temporary jobs and on jobs across the wage distribution. We analyze the effect on the employment percentage change between the time of the ENHAT interview (late 2017 and early 2018) and December 2020.

We identify the effect of new technology use, the main explanatory variable, using two alternative definitions. First, we include a dummy variable for whether the firm adopts

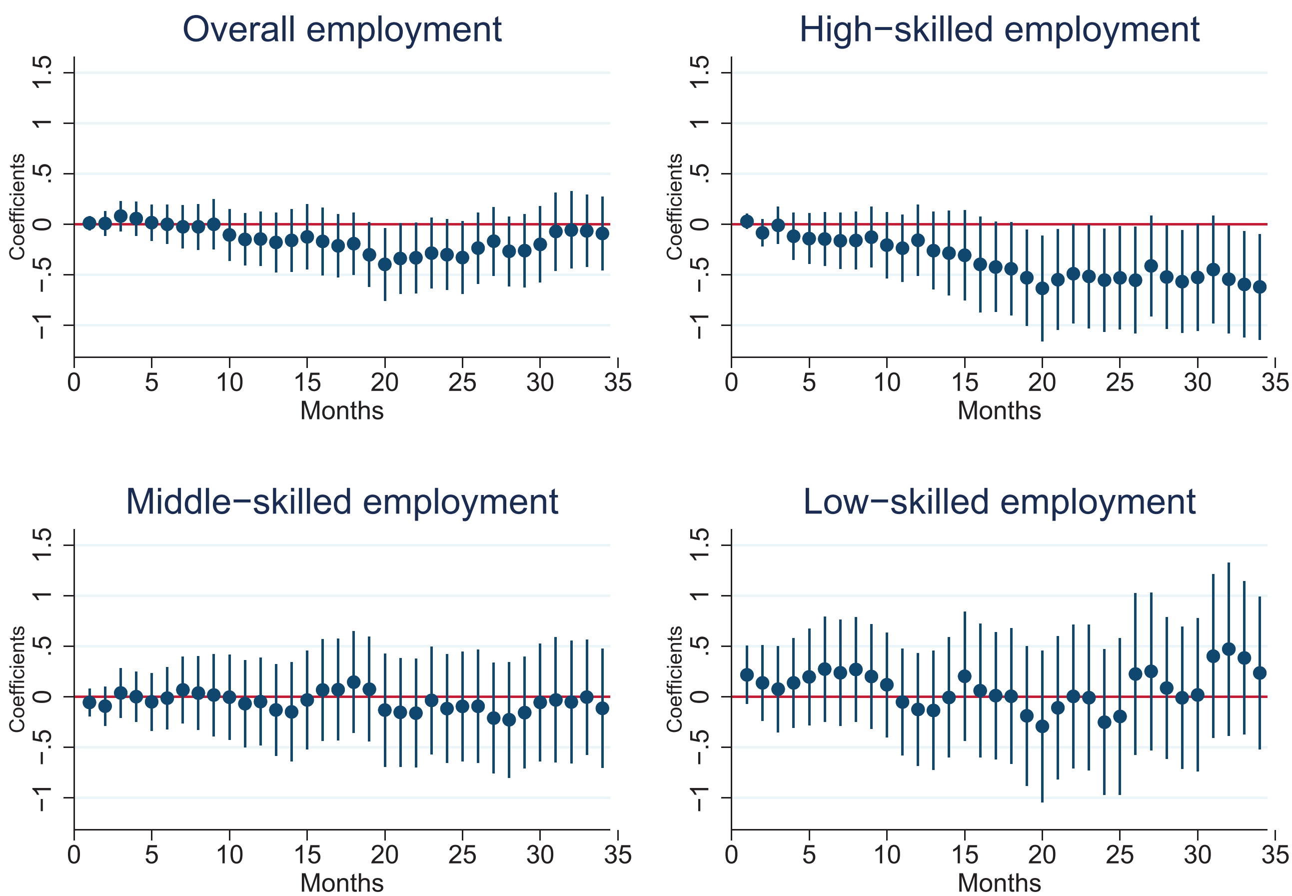

Figure 2. The effect of using at least one new technology on labor demand by months. *Notes*: The vertical axis corresponds to the IV estimation of β using and (2). The outcome variable is the percentage change of employment between Month 0 (when the technology adoption is observed) and month *i*, where *i* varies each month. The instrument is the change in the number of internet satellite parabolic antennas from 2007 to 2012 in each municipality. Dots are point estimates, and vertical lines are 95% confidence intervals. All regressions control for the following characteristics: the number of workers in 2017–8, the number of workers in 2011–2, firm's age, firm located in a large city, years in the current location, one-digit economic sector fixed effects, and month fixed effects.

at least one of the following new technologies: AI, advanced robotics, autonomous transport, advanced manufacturing, 3D printing, or advanced network services. Second, we analyze the effect of disaggregated technologies on labor demand. The limited number of firms using some technologies (Table 1) constrains us to conduct the analysis on the two most commonly used technologies only: AI and advanced network services.

5. Results

5.1 At least one new technology

We first present the estimated effects of new technology adoption on labor demand using the change in the number of internet satellite parabolic antennas at the municipality level as an IV. Figure 2 shows four graphs where the horizontal axis corresponds to the months after ENHAT data were collected (i.e. the data collection month is set to 0) and the vertical axis corresponds to the IV coefficient where the outcome is the percentage change of employment with respect to the outcome at Month 0. Dots are point estimates, and vertical lines are 95 per cent confidence intervals. Overall, we find a slightly negative effect of technology adoption on aggregated labor demand that activates around 20 months after we observe the use of new technologies. These results are driven by a negative effect on the demand for high-skilled workers. Moreover, the negative effect on the demand for high-skilled workers becomes more pronounced during the COVID-19 pandemic. In contrast, there is no sign of any effect on the demand for middle- and low-skilled workers.[15]

Table 3 reports the point estimate, the first-stage coefficient of technology adoption, and the robust first-stage F-statistic for three periods: 1, 2, and 3 years after the technology adoption. The first-stage results show that, as expected, a larger access to the internet in the district where the firm is located increases the likelihood of firms adopting new technologies. Associated with this, the effective F-statistic is above 23, which always rejects the null hypothesis of weak instruments (Olea and Pflueger 2013).[16] Therefore, the relevance condition for a valid IV is justified.

Table 3 shows that the effect on overall employment is not significant within the first year but becomes significant after two years, and in high-skilled labor both after two and three years. In particular, firms using technologies decreased their employment growth by 30 per cent in total employment and 55 per cent in high-skilled workers after 2 years and 75 per cent in high-skilled workers after 3 years.

Regarding our other outcomes, we find that the adoption of at least one new technology negatively affects the demand for professionals and technicians (Fig. 3). The effect on the employment growth of administrative and service and sales workers is also negative but is imprecisely estimated. In contrast, a positive effect is found on the demand for workers in elementary occupations, but, again, the results are not statistically significant. Table A1 in the Supplementary Appendix shows that the first-stage coefficients are highly significant and

Table 3. Effect of using at least one technology on labor demand using the IV (two-stage least-squared regression).

	Overall employment	High-skilled employment	Middle-skilled employment	Low-skilled employment
12 months after the survey interview				
At least one technology	−0.14	−0.16	−0.05	−0.12
	(0.14)	(0.18)	(0.22)	(0.29)
First stage				
Change in the number of internet satellite antennas (hundreds)	0.27***	0.26***	0.27***	0.29***
	(0.05)	(0.05)	(0.05)	(0.05)
Observations	2,144	2,008	1,755	1,756
R^2	−0.01	0.00	0.01	0.02
Effective F-statistic	32.12	28.41	28.37	28.41
24 months after the survey interview				
At least one technology	−0.30*	−0.55**	−0.12	−0.25
	(0.18)	(0.26)	(0.27)	(0.37)
First stage				
Change in the number of internet satellite antennas (hundreds)	0.27***	0.26***	0.27***	0.27***
	(0.05)	(0.05)	(0.05)	(0.06)
Observations	2,054	1,942	1,723	1,721
R^2	−0.07	−0.15	0.01	0.01
Effective F-statistic	30.28	27.21	27.17	23.92
36 months after the survey interview				
At least one technology	−0.11	−0.75***	−0.04	0.58
	(0.19)	(0.29)	(0.29)	(0.40)
First stage				
Change in the number of internet satellite antennas (hundreds)	0.30***	0.29***	0.29***	0.30***
	(0.05)	(0.05)	(0.05)	(0.06)
Observations	1,884	1,804	1,609	1,601
R^2	0.04	−0.21	0.03	−0.04
Effective F-statistic	35.05	30.94	29.88	27.20

Notes: Standard errors (SEs) are in parentheses. * Significant at 10%, ** significant at 5%, and *** significant at 1%. The outcome variable is the percentage change of employment between Month 0 (when the technology adoption is observed) and Months 12, 24, and 36, respectively. The instrument is the change in the number of internet satellite parabolic antennas from 2007 to 2012 in each municipality. All regressions control for the following characteristics: the number of workers in 2017–8, the number of workers in 2011–2, firm's age, firm located in a large city, years in the current location, one-digit economic sector fixed effects, and month fixed effects. The effective F-statistic is calculated following Olea and Pflueger (2013).

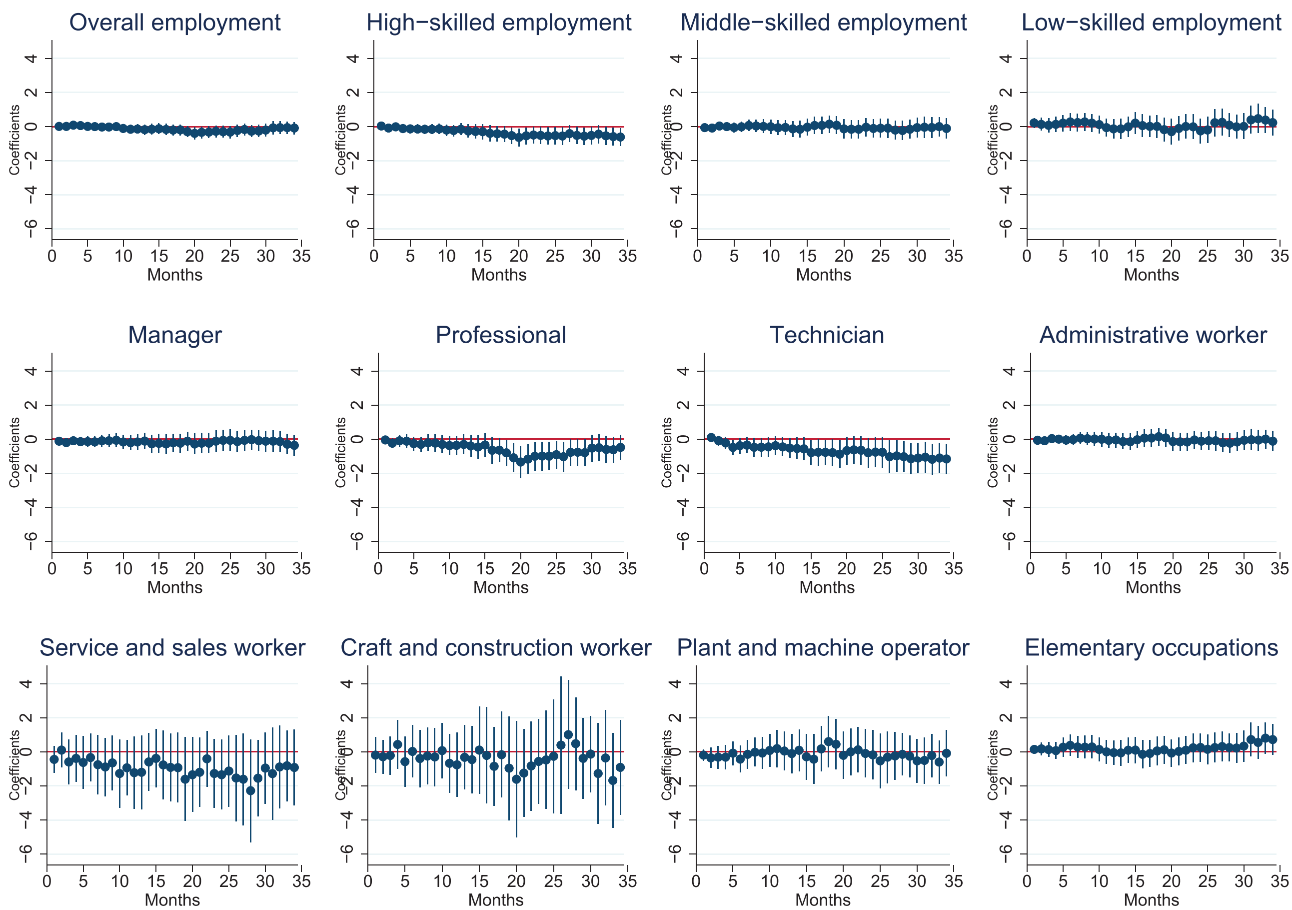

Figure 3. The effect of using at least one new technology on labor by occupations and months. *Notes*: The vertical axis corresponds to the IV estimate using and (3). The outcome variable is the percentage change of employment between Month 0 (when the technology adoption is observed) and month *i*, where *i* varies each month. The instrument is the change in the number of internet satellite parabolic antennas from 2007 to 2012 in each municipality. Blue dots are point estimates, and blue vertical lines are 95% confidence intervals. All regressions control for the following characteristics: the number of workers in 2017–8, the number of workers in 2011–2, firm's age, firm located in a large city, years in the current location, one-digit economic sector fixed effects, and month fixed effects.

that the effective *F*-statistic rejects the null of weak instrument considering a 20 per cent of a worst-case bias for all occupations, except for service and sales workers, agricultural workers, craft and construction workers, and plant and machine operators.

When looking at the effect of technology adoption on labor demand classified by the level of routineness, we find no effects on routine and non-routine manual jobs or on routine cognitive jobs. Contrarily, we find that technology adoption negatively affects non-routine cognitive jobs (Figure A3 in the Supplementary Appendix).[17] Analyzing the effect according to the type of job contract, we find negative and significant effects only for temporary job contracts (Figure A4 in the Supplementary Appendix), which is consistent with Viollaz (2018). In particular, the adoption of new technology decreases the temporary employment growth rate by 64 per cent after 20 months.[18]

5.2 AI and advanced network services

We next turn to investigate the effect of the adoption of specific technologies on labor demand. Considering the low levels of technology adoption and the relatively small sample size, we are not able to make inferences for each technology separately. However, we can explore whether effects vary between the two most commonly used technologies, that is AI (4 per cent) and advanced network services (25 per cent). Table 4 shows the effects of these two technologies on labor demand using our IV approach.

Interestingly, in the medium term, we find negative and significant effects of both technologies on the demand for workers, particularly among the high-skilled. Although the first stage is coherent with our IV approach, our instrument is weak for the use of AI (effective *F*-statistics is 8.82) but not for the use of advanced network services (effective *F*-statistics is 26.46). This reflects that the instrument provides a proper measure of advanced network services but is not strongly associated with the adoption of AI. This is a reasonable finding to the extent that advanced network services are more associated with information technologies such as cloud computing, big data, or the internet of things, which are heavily dependent on internet connection. In contrast, AI involves technologies that are able to perceive their environment and learn and carry out tasks intelligently such as ML, natural language processing, and image or speech recognition. These are not necessarily dependent on internet connection.[19]

Table 4. Effects of using AI and advanced network services on labor demand using IV (two-stage least-squared regression).

	AI				Advanced network services			
	Overall employment	High-skilled employment	Middle-skilled employment	Low-skilled employment	Overall employment	High-skilled employment	Middle-skilled employment	Low-skilled employment
12 months after the survey interview								
At least one technology	−0.43	−0.47	−0.13	−0.43	−0.15	−0.16	−0.05	−0.13
	(0.43)	(0.56)	(0.63)	(1.00)	(0.14)	(0.19)	(0.24)	(0.30)
First stage								
Change in the number of internet satellite antennas (hundreds)	0.09***	0.09***	0.10***	0.08***	0.25***	0.25***	0.26***	0.27***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.06)
Observations	2,144	2,008	1,755	1,756	2,144	2,008	1,755	1,756
R^2	−0.03	−0.04	0.01	0.01	−0.02	0.00	0.01	0.01
Effective *F*-statistic	10.23	8.79	9.70	6.81	28.41	25.88	24.94	24.74
24 months after the survey interview								
At least one technology	−0.85	−1.59*	−0.31	−0.81	−0.31*	−0.56**	−0.12	−0.26
	(0.57)	(0.85)	(0.73)	(1.26)	(0.19)	(0.27)	(0.28)	(0.38)
First stage								
Change in the number of internet satellite antennas (hundreds)	0.09***	0.09***	0.10***	0.08**	0.26***	0.26***	0.26***	0.26***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.06)
Observations	2,054	1,942	1,723	1,721	2,054	1,942	1,723	1,721
R^2	−0.14	−0.34	0.01	−0.03	−0.08	−0.16	0.01	0.01
Effective *F*-statistic	10.34	8.88	10.15	6.30	27.83	26.17	25.26	22.25
36 months after the survey interview								
At least one technology	−0.30	−2.12**	−0.11	1.95	−0.11	−0.78**	−0.04	0.61
	(0.53)	(0.93)	(0.78)	(1.45)	(0.19)	(0.30)	(0.31)	(0.42)
First stage								
Change in the number of internet satellite antennas (hundreds)	0.11***	0.10***	0.11***	0.09**	0.28***	0.28***	0.28***	0.28***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.06)
Observations	1,884	1,804	1,609	1,601	1,884	1,804	1,609	1,601
R^2	0.04	−0.44	0.03	−0.17	0.05	−0.22	0.03	−0.05
Effective *F*-statistic	11.43	10.10	10.56	6.53	31.57	28.89	26.99	24.24

Notes: Standard errors (SEs) are in parentheses. * Significant at 10%, ** significant at 5%, and *** significant at 1%. The outcome variable is the percentage change of employment between Month 0 (when the technology adoption is observed) and Months 12, 24, and 36, respectively. The instrument is the change in the number of internet satellite parabolic antennas from 2007 to 2012 in each municipality. All regressions control for the number of workers in 2017–8, the number of workers in 2011–2, firm's age, firm located in a large city, years in the current location, one-digit economic sector fixed effects, and month fixed effects. The effective *F*-statistic is calculated following Olea and Pflueger (2013).

We also estimate the model for the other labor demand outcomes considered in the paper.[20] By major occupational group, we find, again, that effects on professionals drive the negative results. Regarding the type of job contract, we find negative results on temporary jobs for the months preceding the 2-year period. We did not find a clear pattern, or significant effects, across the wage distribution, and we failed to find strong evidence for the job displacement hypothesis by wage distribution or job routineness. Technological progress in Peru might be at an early stage, so its effects on the labor market differ from the ones in developed countries, in which job automation is a current concern. However, our results are aligned with previous evidence that technology adoption in Peru does not have a negative effect on middle-wage workers or routine workers (Maloney and Molina 2016; Messina and Silva 2017).

5.3 Robustness checks

Our IV identification strategy would be invalid if the instrument captures district-level characteristics correlated with labor demand. Our instrument captures the net effect of internet availability, as it corresponds to the change in the number of internet satellite antennas at the district level. However, it is possible that it could be correlated with other municipality-level trends that make our exclusion restriction invalid. To account for this, we regress our instrument using supply and demand factors potentially correlated to labor demand in each district, using the following specification:

$$internet_d = \alpha + factors * \beta + u_d + \varepsilon_{dt} \qquad (3)$$

where $internet_d$ is the number of internet satellite antennas in the district d and $factors$ are a set of time-variant district-level characteristics, including the percentage of high-skilled workers, population size, number of workers, number of firms, and the percentage of firms in manufacturing, trade, construction, and other services economic sectors. u_d is the district fixed effect, which considers the unobserved time-invariant heterogeneity. We confirm that none of the explanatory variables are significant (Table A2 in the Supplementary Appendix), which suggests that internet availability is unlikely to be related to factors relevant to labor demand. Moreover, the results of the IV estimation are robust when we include the change in time-variant district factors as additional explanatory variables (Table A3 in the Supplementary Appendix).

Our results might be misleading if technology-producing firms are driving the effects of technology on employment because we are focusing on technology-using firms. The technology-producing sector usually has high productivity levels and might raise employment as a result of the direct benefit of broadband availability. To account for this, we estimate, excluding firms in the ICT sectors. Results in Table A4 in the Supplementary Appendix confirm that our results are not driven by technology-producing firms.

We can also test our exclusion restriction by performing the IV estimation in a subsample of never-taker and always-taker firms. Never-taker firms are firms that never take the treatment (i.e. technology adoption) regardless of the value of the instrument (i.e. number of internet satellite antennas), and always-taker firms are firms that always take the treatment regardless of the value of the instrument. These firms should not have any effect on their employment outcomes when estimating the IV regression. If we found a significant effect, then broadband availability would be producing an effect on employment through other channels than technology adoption, which would violate our exclusion restriction. We define always-taker firms as firms that adopt new technology in districts where the change in the number of satellite antennas is in the bottom fifth percentile. Similarly, never-taker firms are those that do not adopt new technology and are located in districts where the change in the number of satellite antennas is in the top 95th percentile. As shown in Table A5 in the Supplementary Appendix, there are no effects on any outcome, which supports the validity of our exclusion restriction.

6. Conclusion

Forecasts about the effects of new technologies on labor demand are generally pessimistic, particularly for low-skilled workers and those whose occupations mainly involve routine tasks. This paper exploits a national representative employer survey and administrative data in Peru to offer empirical evidence about the current use of new technologies and its effects on labor demand in a developing country.

We find that the use of new technologies among formal firms in Peru is still incipient and is mainly driven by larger and older firms. Also, we find that the use of new technologies affects the skills demand in the mid-term. New technology adoption slightly reduces the demand for high-skilled workers in non-routine cognitive occupations, professionals and technicians, and those with temporary job contracts. Overall, this evidence suggests that firms adopting new technologies in Peru use technologies as a substitute for some high-skilled workers.

It is important to highlight that our results are based on a sample of the 'top' firms in Peru: small, medium, and large formal firms, representing only 2 per cent of the total number of firms in the country. Including micro formal and informal firms (39 and 59 per cent of total firms, respectively), which are presumably more precarious than the small formal firms included in the sample, would further reduce the proportion of firms using new technologies in the country and the estimated average effect on labor demand. Although these firms employ 19 per cent of the total workforce and their contribution to the gross value added is 93 per cent (Ministerio de la Producción 2018), we are not extrapolating the results for the whole economy.

The low rate of technology adoption found among firms in Peru represents an opportunity to apply public policies of prevention before automation becomes widespread, like in developing countries. Two main public policies are drawn from this study. First, given the results on high-skilled workers' demand, it is important for Peru to work further on their education system in order to improve skills that are difficult to be replaced by technology (e.g. socio-emotional skills). Second, as low-skilled and routine manual workers are likely to be displaced by automation technology, training policies that update their skills, or programs to change the tasks at their work completely, are desirable measures for those workers to not lose their jobs. In this regard, skills necessary for continuous learning and skills that are automatable at a higher cost (e.g. socio-emotional and digital skills) might be particularly important.

Supplementary material

Supplementary material is available at *Science and Public Policy* online.

Data Availability

The survey data (ENHAT) that support the findings of this study are available on request from the corresponding author. Due to the nature of the research, due to legal restrictions, administrative data is not available.

Conflict of interest statement. None declared.

Notes

1. To the best of our knowledge, there are two databases containing information about AI technologies. The first one covered fourteen economic sectors and ten countries across Europe, North America, and Asia (McKinsey Global Institute 2017). The second one is the Annual Business Survey from the USA (Zolas et al. 2021).
2. In terms of the technology adoption indicator of the Global Competitive Report (World Economic Forum 2018), Peru's score is 44, while the average of Latin American and Caribbean countries, and the one for all developing countries combined, is 46. In addition, Peru's Global Innovation Index score (32) is also close to the average score of Latin American countries and developing countries combined (30) (Cornell University, INSEAD & WIPO 2018).
3. Autor and Salomons (2018) argue that technological advances might also produce direct-industry effects, between-industry effects, final demand effects, and indirect effects through input–output linkages.
4. An offshorable job does not have to be done at a specific location and does not require face-to-face personal communication. Recent technological advances have dramatically lowered the cost of offshoring information-based tasks to foreign worksites. For instance, about 25 per cent of occupations in the USA are 'offshorable' (Blinder and Krueger 2013).
5. Similar to Frey and Osborne (2017), in this paper, computerization refers to automation by means of computer-controlled equipment.
6. The sampling frame contained 90,534 firms listed in 2016 in the Central Directory of Companies and Establishments from the National Superintendency of Customs and Tax Administration (SUNAT) and the INEI. Formal firms in Peru represent 41 per cent of total firms in the country. Additionally, firms in the sample were selected among those whose net annual sales in 2016 were above USD 175,445 or 150 tax units. Consequently, microenterprises, which represent 95 per cent of the formal firms in Peru (Ministerio de la Producción 2018), are not included in the ENHAT.
7. Excluded firms are similar in key variables, such as technology adoption and belonging to an economic sector, but are, on average, smaller than the firms remaining in the sample. The main reason for this is that our empirical strategy uses information of firms that survive long periods (2011–20), which are usually large firms.
8. We choose this measure of firm size because it is defined that way in the current Peruvian laws. Moreover, firms are treated by law differently according to this measure of firm size.
9. PE is an employer–employee administrative payroll dataset in Peru. Since 2008, firms are legally required to upload information of their employees on the Peruvian tax authority's website. When new workers are hired, firms report job and worker information in the PE. This dataset contains information of nearly 3.5 million workers linked to nearly 300,000 firms (MTPE 2017). Similar to the ENHAT, it excludes the public sector but includes firms in the agricultural sector and formal microenterprises. Moreover, wage and payroll data correspond to the end-of-the-month net wage (i.e. excluding payments to the pension system, bonuses, and other atypical payments to the worker) in the period the worker is linked to the firm.
10. Due to confidentiality, this merge was performed directly by the Ministry of Labor of Peru.
11. Other proxies of broadband internet availability, such as the percentage of households with internet access at the local level (Akerman et al. 2015), might not be adequate since labor demand is strongly correlated to household characteristics.
12. In 2012, the Government of Peru declared that the deployment of fiber optic networks, which provides faster speed and more reliable internet connection than standard broadband, was a national priority through the Law No. 29904 (Ley de Promoción de Banda Ancha y Construcción de la Red Dorsal Nacional de Fibra Óptica).
13. Using this definition, the non-routine cognitive and high-skilled job categories coincide.
14. Due to data constraints, we rely on cross-sectional data for routine task content. See Ross (2020) for a panel data analysis of the effect of technological change on employment outcomes.
15. We perform a naïve regression using ordinary least squares (OLS) to see the effect of new technology adoption on labor demand. For this, we estimate without considering the first stage (to predict the technology adoption. Results are shown in Figure A1 in the Supplementary Appendix. We find that the OLS estimate differs from the IV estimate. OLS estimates produce an upward bias estimation of the impact of new technology.
16. In the case of one endogenous regressor, the effective *F*-statistic rejects the null of a weak instrument when it exceeds 15.1 considering a 20 per cent of a worst-case bias; 23.1 considering a 10 per cent of a worst-case bias; and 37.4 considering a 5 per cent of a worst-case bias. This test is robust to heteroscedasticity.
17. As mentioned previously, by definition, this category coincides with high-skilled jobs.
18. Analyzing the effect of technology adoption on labor demand across the wage distribution, we find that the effects are mostly negative but statistically insignificant (Figure A2 in the Supplementary Appendix), except for workers at the eighth decile who are negatively affected after the eighth month.
19. We also use the value of AI occupational impact (Felten et al. 2018) in 2011–2 as an instrument for AI technology, but it proves to be even weaker.
20. Results are available upon request.

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