IDB WORKING PAPER SERIES Nº IDB-WP-01013

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Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library
Novella, Rafael.
Are we nearly there yet?: new technology adoption and labor demand in Peru / Rafael Novella, David Rosas, Alfredo Alvarado.
p. cm. — (IDB Working Paper Series ; 1013)
Includes bibliographic references.
1. Labor demand-Effect of automation on-Peru. 2. Automation-Economic aspects-Peru. 3. Labor productivity-Effect of technological innovations on-Peru. I. Rosas-Shady, David. II. Alvarado, Alfredo. III. Inter-American Development Bank. Labor Markets Division. IV. Title. V. Series.
IDB-WP-1013

http://www.iadb.org

Are We Nearly There Yet? New Technology Adoption and Labor Demand in Peru†

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Abstract

Forecasts about the effect of new technologies on labor demand are generally pessimistic. However, little is known about the current level of adoption and the effect on labor demand, particularly in developing countries. This paper exploits a recent employer survey in Peru to offer empirical evidence in these regards. Our results show that although the adoption of new technologies by firms is still incipient, it increases the labor demand of higher-skilled workers and does not affect the demand of the low-skilled. However, we find a negative effect on the demand for workers in routine manual tasks occupations. The adoption of new technologies will possibly increase in Peru. Meanwhile, it is important to keep investing in workers' skills, so they become less automatable and more productive.

Keywords: automation, labor demand, employer survey.

JEL codes: O33, J23, J24.

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† We thank Carolina González-Velosa, Marco Manacorda, Oscar Mitnik, Laura Ripani, Graciana Rucci and an anonymous referee for helpful comments.

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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 & Michaels, 2018). Forecasts about the effects of the adoption of these technologies on labor outcomes are divergent but mainly pessimistic (Pew Research Center, 2017), particularly for developing countries, where about two out of three jobs are expected to experience significant automation (World Bank, 2016). In contrast, evidence about the current effect of new technologies adoption on labor demand is still scarce, in part due to the lack of specific firm-level data about the use of these technologies (Seamans & Raj, 2018).[1] Using a recently collected national representative employer survey in Peru: the *Encuesta Nacional Habilidades al Trabajo* (ENHAT) (Novella, Alvarado, Rosas, & González-Velosa, 2019),[2] this paper offers empirical evidence about the current adoption level of new technologies and its effects on labor demand in a developing country.

Studying the degree of adoption of these technologies and their 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 at improving their productivity and competitiveness in local and global markets. Second, it allows the identification of groups of workers and firms that might suffer from the irruption of new technologies. Third, it provides information for the design of public policy interventions aimed at improving countries' productivity and development.

The available recent empirical studies show divergent results. While some estimate that around 47 percent of employment in the US is at risk of automation (Frey & Osborne, 2017), others indicate that only 14 percent of jobs are at high risk of automation across the OECD (OECD, 2019). Estimates for low- and middle-income countries are, in general, worrisome. For instance, in Uruguay and Argentina, it is estimated that 66 and 64 percent of the workforce, respectively, would be replaced by automation technologies (Aboal & Zunino, 2017). Similarly, more than half of all jobs in the Association of Southeast Asian Nations (ASEAN) are at high risk of displacement due to technology over the next decade or two (Chang & Huynh, 2016).

Peru offers an interesting setting for studying the effect of new technologies adoption on labor outcomes. It is estimated that 53 percent of jobs in the country are at risk of automation, which is the highest figure in South America (Chui, Manyika, & Miremadi, 2017). Although the recent 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, Cristia, Hincapie, Messina, & Ripani, 2017). The lack of human

[1] Other recent studies analyze the effect that automation would have on productivity (Graetz & Michaels, 2018), job quality (Menon, Salvatori, & Zwysen, 2018) and job duration (Silva & Lima, 2017).

[2] To the best of our knowledge, the other database containing information about AI or other automation technologies is the one presented in the McKinsey Global Institute report 2017 that covered 14 economic sectors and ten countries across Europe, North America, and Asia (McKinsey Global Institute, 2017).

capital explains that almost half of the firms in Peru struggle to fill in their vacancies (Novella et al., 2019). In this scenario, firms can consider substituting low-skilled workers by new technologies to increase productivity. In turn, displaced workers would end up in lower-quality jobs or unemployment, which accentuate the already high inequality observed in the country.

We use kernel propensity score matching (PSM) and instrumental variables (IV) methods to estimate the effect of new technologies adoption on labor demand. For the first method, identification relies on the assumption that the selection of firms into adopting new technologies is based on observables characteristics. We furtherly estimate the effect of using new technologies on labor demand, by using the availability of broadband Internet in the municipality where the firm is located as an instrument. Under both methods, our outcomes of interest correspond to having at least a job vacancy, having vacancies by skill level (high, medium, and low), having vacancies by task level (non-routine cognitive, routine cognitive, non-routine manual, and routine manual) and the probability of computerization of these vacancies (Frey & Osborne, 2017).[3]

We find that only about one quarter (27 percent) of formal firms in Peru has adopted new technologies. On average, these firms are larger, older and more linked to foreign business groups and markets and have larger market power, innovation capacity and productivity than non-adopting firms. Moreover, we find that the use of new technologies is positively associated with labor demand. In contrast to comparable firms, those using new technologies are more likely (4 percentage points, pp) to have at least one job vacancy, particularly for high- and middle-skilled occupations (5 and 2 pp, respectively). Conversely, the demand for low-skilled occupations and along the distribution of the computerization probability are similar among the two types of firms. Moreover, firms using new technologies are more likely to have vacancies with a larger component of non-routine cognitive tasks and less likely to have vacancies with a larger component of routine manual tasks. These results hold when we look at the effect of using new technologies on labor demand, using an IV approach.

The still incipient use of new technologies among Peruvian firms and the reduced effects on labor demand might change in the future. For instance, we find that 35 percent of firms expect to adopt new technologies in the next 3 years. In the meantime, low and middle-income countries, such as Peru, have the chance to strengthen the investment in human capital to provide their workers with 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, Section 6 concludes.

[3] Similar to Frey and Osborne (2017), in this paper computerization refers to automation by means of computer-controlled equipment.

2. New technology and labor demand

Technological change might affect labor demand through three main channels (Gregory, Salomons, & Zierahn, 2016). First, it might reduce labor demand through a substitution effect: reductions in the cost of capital lead firms in the high-tech tradable sector to substitute capital for labor inputs. Second, technological change might increase labor demand through a product demand effect: reductions in the cost of capital, and consequently in the price of tradables, lead to raises in product and labor demand. Third, product demand spillovers 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. Additionally, Autor and Salomons (2018) allow technological advances not only to produce a direct-industry, between-industry and final demand effects but also indirect effects through input-output linkages. The aggregated effect of innovation on employment would vary with the type of innovation (i.e., process or product) and the associated displacement (e.g., process innovations reducing employment) and compensation effects (i.e., related to changes in the demand for products) (Harrison, Jaumandreu, Jacques, & Peters, 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, Katz, & Krueger, 1998; Autor, Katz, & Kearney, 2008; Carneiro & Lee, 2011). However, this approach fails in explaining several stylized facts such as job polarization (Acemoglu & Autor, 2011), the substitution of workers in certain tasks (Autor, Levy, & Murnane, 2003; Cortes & Salvatori, 2019) and offshorability (Blinder & Krueger, 2013).[4] The second approach, developed by Acemoglu and Restrepo (2018), intends to overcome these deficiencies. They 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 increase productivity, which increases the demand for labor in non-automated tasks. Moreover, sectors and occupations non-directly affected by the technological change might expand after absorbing the labor freed from those sectors and occupations affected by the technological change. Finally, the authors show that productivity improvements due to new machines may even expand employment in affected industries (Acemoglu & Restrepo, 2016; 2018).

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 affect jobs involving routine tasks. Declines in the cost of using information and communications technologies and the productivity improvements associated with it might lead firms to substitute workers performing

[4] An offshorable job does not have to be done at a specific location and does not requires face-to-face personal communication. The recent technological advances have dramatically lowered the cost of offshoring information-based tasks to foreign worksites. For instance, about 25% of occupations in US are "offshorable" (Blinder & Krueger, 2013).

routine or codifiable tasks by technology. This could be the case for some of the tasks (e.g., production and administrative manual tasks) of middle-skilled workers (Michaels, Natraj, & Van Reenen, 2014). In contrast, new technologies might not affect the two extremes of the skills distribution. At the one hand, new technologies are expected to be a complement of high-skilled or managerial, professional, technical and creative occupations. At 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 & Autor, 2011; Autor & Dorn, 2013).

What tasks are automatable is constantly challenged by the advances of new technologies. Brynjolfsson and McAfee (2012) argue that new technologies might replace humans in tasks beyond the routine manual ones. As an example, they mention that driving cars was considered a non-manual routine task, which is now fully automatized by autonomous transport technology. In this context, Frey and Osborne (2017) expand and update the routine-tasks 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 United States, they estimate the probability of computerization of 702 occupations. They estimate that around 10 percent of the occupations are already fully computerizable.

Empirical evidence about both the current level of new technologies adoption and its effect on labor demand are scarce. The available evidence mainly focuses on the effect of information and communications technology (ICT). Akerman, Gaarder and Mogstad (2015) find that broadband adoption by firms increases the wages of skilled workers, mainly by performing non-routine abstract tasks. Other automation technologies, such as programmable controllers, computer-automated design, and numerically controlled machines do not markedly affect wages and employment in manufacturing firms (Doms, Dunne, & Troske, 1997). Through a proxy of technological exposure, Montresor (2019) finds that while technological change has substituted routine labor, it has not affected non-routine skilled employment. In Latin America, investments in ICT in Argentina (Brambilla & Tortarolo, 2018) and Internet use in Mexico (Iacovone & Pereira-Lopez, 2017) have increased the demand for both low- and high-skilled workers, but particularly for the latter group. In contrast, Internet availability in Brazil did not affect overall employment and even affect the demand of low-skilled workers by replacing routine tasks (Almeida, Corseuil, & Poole, 2017; Dutz, Mation, O'Connell, & Willig, 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). 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, Fernandes, & Viollaz, 2017). Moreover, Crespi and

Tacsir (2013) show evidence of skill-biased product innovation in a sample of four Latin American countries.

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 so far relied on indirect proxies of automation, such as routine task input (Autor et al., 1998, 2008; Autor et al., 2003; Goos & Manning, 2007; Autor & Dorn, 2013; Autor, Dorn & Hanson, 2015), investment in computer capital (Beaudry, Doms & Lewis, 2010; Michaels et al., 2014), investment in robots (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2017) or patent grant texts (Mann & Püttmann, 2017). However, these proxies present shortcomings at 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 classification (Seamans & Raj, 2018). Patent grant texts classification is an inherently imprecise activity and might introduce further inaccuracies through probabilistic matchings of patents to industries and commuting zones (Mann & Püttmann, 2017). ENHAT allow us to directly identify the use of new technologies by firms.

3. Data description

The *Encuesta de Habilidades al Trabajo* (ENHAT) is an employer skill survey collected in Peru between 2017 and 2018, which is statistically representative at the national, firm size and sectoral levels. ENHAT was designed to measure skills gap; to understand its causes and consequences from the firms' perspective; and, to understand the strategies adopted by firms to overcome it. A main feature of ENHAT is that it contains detailed information about the adoption of new technologies.

ENHAT surveyed a sample of 4105 small, medium and large formal firms operating in almost all sectors (excluding agricultural and public sectors) in Peru.[5] Due to missing information in key variables, the final sample size corresponds to 3262 firms. The sample is probabilistic, stratified and independent in each of the sections of the International Standard Industrial Classification (ISIC) Revision 4. Inferences can be made at national, firm size or economic sectors levels. Firm size is defined by net annual sales in three categories: small firms (86 percent), with sales between USD175,445 and USD1,988,377; medium-sized firms (3 percent), with sales between USD1,988,377 and USD2,690,158; and large firms (10 percent), with sales above USD2,690,158. Following ILO (2019), we have reclassified the 18 economic sectors included in ENHAT in five sectors: natural resources (including mining, fishing, electricity, and water supply), manufacturing, construction, market services (including trade, transportation, accommodation and food; information and

[5] The sampling frame contained 90 534 firms listed in 2016 in the Directorio Central de Empresas y Establecimientos from the Superintendencia Nacional de Aduanas y de Administración Tributaria (SUNAT) and the Instituto Nacional de Estadística e Informática (INEI). Formal firms in Peru represent 41 percent of total firms in the country. Additionally, firms in the sample were selected among those whose net annual sales in 2016 were above USD175,445 or 150 *Unidades Impositivas Tributarias* (UIT). Consequently, micro-enterprises, which represent 95 percent of the formal firms in Peru (Ministerio de la Producción, 2018) are not included in ENHAT.

communication, financial, real estate, professional, and administrative activities) and non-market services (including education, health, arts and entertainment, and other service activities).

For collecting data on occupations, ENHAT uses the *Clasificador Nacional de Ocupaciones* 2015 (CNO 2015), which is the official classification used in Peru. We reclassified the information of job vacancies, collected at occupation level, in low-, middle- and high-skilled. High-skilled occupations include managers, professionals, technicians, and associate professionals; middle-skilled occupations include clerical support workers; and, low-skilled occupations include jobs in services, sales, agricultural, forestry, fishery, craft, related trades workers, plant and machine operators, assemblers and elementary occupations.

Similarly, using the definition of Cortes and Salvatori (2019), we classified vacancies according to the prevailing routine level of their tasks in: non-routine cognitive (managers, professionals, technicians, and associate professionals);[6] routine cognitive (clerical support workers and sales workers), non-routine manual (care workers, personal services workers, and elementary occupations), and routine manual (agricultural, forestry, fishery, craft, related trades workers, plant and machine operators, and assemblers).

Table 1 shows that firms in ENHAT are mainly small and dedicated to market services (72 percent). They have, on average, 30 workers and 12 years of operation. Also, firms are mainly owned by national capitals, do not export, are not part of a larger business group and do not have a R&D department. Additionally, even though they report a relatively high level of market competition and financial problems, their expectations about future sells are optimistic. We also find that, although internal skills gap is not the main concern (97 percent of firms consider their workers are competent), the external skills gap is considerable large (47 percent of firms struggle to fill in their vacancies) (Novella et al., 2019).

ENHAT also collected information about the use of automation technologies 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 technology (Störmer, et al., 2014; Glenn & Florescu, 2016; World Economic Forum, 2016; Hogarth, 2017): artificial intelligence, advanced robotics, autonomous transport, advanced manufacturing, 3D-printing, and advanced network services.[7]

We find that the use of these new technologies among firms in Peru in 2017-2018 is still incipient, except for ANS (Table 1). On average, only 27 percent of firms use at least one of these technologies and this proportion shrinks to 7 percent when ANS is not considered. Table 1 shows that, on average,

[6] Under this definition non-routine cognitive and high-skilled vacancies are the same.
[7] Unfortunately, ENHAT did not include information about when firms adopted these technologies.

firms using new technologies are larger (in term of the number of workers, sales and being part of a larger business group), 1 year older and more linked to foreign capitals and markets (i.e., export more). They also have more innovation capacity (i.e., R&D), productivity and a better perception of their market power (i.e., fewer competitors).[8] Firms using new technologies have also a larger share of high- and medium-skilled workers and a smaller share of low-skilled workers than other firms.[9] These results are aligned with the findings of Crespi and Zuñiga (2012) for a sample of six Latin American countries.

Regarding the main outcomes, ENHAT also collects information about the firm's current job vacancies. Table 1 shows that 9 percent of firms in the sample have at least one vacancy at the moment of the interview, which is distributed evenly between low-, middle- and high-skilled occupations. In contrast, more firms have vacancies for occupations with a predominantly cognitive rather than manual content. Moreover, as expected, larger firms are more likely to have vacancies and there is large heterogeneity in this variable across economic sectors (Table A1 in the Appendix). Finally, similarly to Chui et al. (2017), we find that job vacancies have an average chance of 54 percent to be automated.

Table 1. Descriptive statistics of the sample

Variable	All		Not using technologies		Using technologies		Sig. mean test
	Mean	(SE)	Mean	(SE)	Mean	(SE)	
Has at least one vacancy	0.09	(0.01)	0.07	(0.01)	0.13	(0.01)	***
Has at least one high-skilled vacancy	0.03	(0.00)	0.02	(0.00)	0.08	(0.01)	***
Has at least one middle-skilled vacancy	0.02	(0.00)	0.01	(0.00)	0.04	(0.01)	***
Has at least one low-skilled vacancy	0.04	(0.00)	0.04	(0.01)	0.05	(0.01)	
Has at least one non-routine cognitive vacancy	0.03	(0.00)	0.02	(0.00)	0.08	(0.01)	***
Has at least one routine cognitive vacancy	0.04	(0.00)	0.04	(0.00)	0.05	(0.01)	*
Has at least one non-routine manual vacancy	0.01	(0.00)	0.01	(0.00)	0.01	(0.00)	
Has at least one routine manual vacancy	0.02	(0.00)	0.02	(0.00)	0.02	(0.00)	
# of vacancies (conditional on having vacancies)	6.12	(1.19)	6.33	(1.92)	5.79	(0.81)	
Probability of computerization (cond. on having vacancies)	0.54	(0.02)	0.55	(0.03)	0.53	(0.03)	
Use of new technologies							
Artificial intelligence	0.03	(0.00)	0.00	(0.00)	0.11	(0.01)	***
Advanced robotics	0.01	(0.00)	0.00	(0.00)	0.02	(0.00)	***

[8] In contrast to firms using only ANS, those using the other new technologies are larger and more likely to export and to have a R&D department or staff. Results are available upon request.

[9] Figure A1 in the Appendix shows that the differences in the shares of high-, medium-, and low-skilled workers between firms using and not new technologies are fairly stable in the period January 2011 – December 2016 and similar to the ones observed in Table 1.

Autonomous transport	0.01	(0.00)	0.00	(0.00)	0.03	(0.01)	***
Advanced manufacturing	0.03	(0.00)	0.00	(0.00)	0.09	(0.01)	***
3D-printing	0.02	(0.00)	0.00	(0.00)	0.06	(0.01)	***
Advanced network services	0.24	(0.01)	0.00	(0.00)	0.88	(0.01)	***
At least one technology	0.27	(0.01)	0.00	(0.00)	1.00	(0.00)	
# of workers (thousands)	0.03	(0.00)	0.02	(0.00)	0.06	(0.01)	***
High-skilled workers (%)	0.42	(0.01)	0.41	(0.01)	0.46	(0.01)	***
Middle-skilled workers (%)	0.17	(0.00)	0.15	(0.01)	0.21	(0.01)	***
Low-skilled workers (%)	0.41	(0.01)	0.44	(0.01)	0.33	(0.01)	***
Years of operations	12.02	(0.18)	11.80	(0.21)	12.73	(0.35)	**
Foreign ownership or control=1	0.04	(0.00)	0.02	(0.00)	0.09	(0.01)	***
Exporting firm=1	0.05	(0.00)	0.04	(0.00)	0.07	(0.01)	***
Firm has more than one economic activity=1	0.20	(0.01)	0.19	(0.01)	0.22	(0.01)	
Firm is a part of a large group=1	0.07	(0.00)	0.04	(0.00)	0.15	(0.01)	***
Sales will grow=1	0.75	(0.01)	0.74	(0.01)	0.80	(0.01)	***
Has important competitors=1	0.68	(0.01)	0.70	(0.01)	0.63	(0.02)	***
Demand depends on prices set by company=1	0.62	(0.01)	0.61	(0.01)	0.65	(0.02)	
R&D department or employees=1	0.16	(0.01)	0.12	(0.01)	0.28	(0.02)	***
Has financial obstacles=1	0.36	(0.01)	0.34	(0.01)	0.38	(0.02)	*
% competent workers	0.97	(0.00)	0.97	(0.00)	0.96	(0.00)	**
Ratio vacancies/workers (cond. on having vacancies)	0.24	(0.02)	0.29	(0.03)	0.18	(0.02)	**
Total factor productivity	8.89	(0.03)	8.83	(0.04)	9.03	(0.05)	***
Firm size							
Large	0.10	(0.00)	0.08	(0.00)	0.16	(0.01)	***
Medium	0.03	(0.00)	0.03	(0.00)	0.05	(0.01)	***
Small	0.86	(0.00)	0.89	(0.01)	0.79	(0.01)	***
Economic sector							
Natural resources	0.03	(0.00)	0.03	(0.00)	0.03	(0.00)	
Manufacturing	0.11	(0.01)	0.10	(0.01)	0.13	(0.01)	**
Construction	0.07	(0.01)	0.07	(0.01)	0.07	(0.01)	
Market services	0.72	(0.01)	0.73	(0.01)	0.68	(0.02)	**
Non-market services	0.07	(0.00)	0.07	(0.00)	0.09	(0.01)	*

Source: ENHAT 2017-18.

Note: Calculations using ENHAT sample weights. Standard errors in parentheses. Significance for mean tests between firms not using and using new technologies: *significant at 10%, **significant at 5%, ***significant at 1%.

As expected, the use of new technologies increases with firm size (Table A1 in the Annex). The use of new technologies among large firms is almost twice as large as the one among small firms. Also, while firms in the manufacturing sector (33 percent) are the ones using new technologies predominantly, firms in the market services sector (26 percent) are the ones using them less.

4. Empirical analysis

Identifying the effect of technology adoption on labor demand is not straightforward, particularly with cross-section data. A potential source of endogeneity is due to the reverse causality of labor demand and technological adoption. To overcome this, we use, as dependent variables, information about the current job vacancies the firm has at the time of the interview, rather than the current stock of workers. Thus, we rule out the chance of labor demand affecting technological adoption. Another source of endogeneity relates to technological adoption being potentially determined by unobserved characteristics that also affect labor demand.

The absence of an exogenous variation for technological adoption imposes challenges to the identification of its causal effects on labor demand. Our first identification strategy relies on assuming that selection is exclusively based on observable characteristics and that common support exists.[10] Thus, we estimate the average treatment effect on the treated (ATT) by kernel propensity score matching (Caliendo & Kopeinig, 2008; Imbens & Wooldridge, 2009):

$$ATT = E\{E[Y1|D = 1, p(X)] - E[YO|D = 0, p(X)]|D = 1\}$$

where p(X) is the probability of using new technologies given a set of X covariates; Y1 and Y0 are potential labor outcomes for firms using new technologies or not, respectively; and D is an indicator for whether a firm uses new technologies.

We define four sets of dependent variables to explore how new technology adoption might affect labor demand. First, we estimate the effect over the probability of the firm having at least one job vacancy. Second, we estimate the effect over the probability of having at least a high-skilled, a medium-skilled or a low-skilled vacancy, separately. Third, we estimate the effect on the probability of having at least a vacancy classified as a non-routine cognitive, a routine cognitive, a non-routine manual or a routine manual, separately (Cortes & Salvatori, 2019). Finally, we estimate the effect on current job vacancies, according to their chances of being computerizable, following Frey and Osborne (2017).[11]

Following Frey and Osborne (2017), we use the probability of automation of the job vacancies in the fourth dependent variable. We follow several steps to assign the 702 computerization probabilities calculated by the authors to the vacancies collected in ENHAT. First, we used the Bureau of Labor Statistics' correspondence table that converts the UK's 2010 Standard Occupational Classification system (SOC 2010), which are used by Frey and Osborne (2017), into the International Standard Classification of Occupations 2008 (ISCO-08). Second, we merged the latter with the INEI's

[10] Figure A2 in the Appendix shows the post-matching common support for each of the four treatment variables.

[11] We also used others measures of labor demand related to automation, such as the routine task index proposed by Goos, Manning, and Salomons (2014) and the offshorability index by Blinder and Krueger (2013). However, we do not find any evidence of significant effects. Results are available upon request.

correspondence table that converts ISCO-08 into CNO 2015. Finally, for each firm, we computed the average probability of automation among the job vacancies, weighted by the number of vacancies in each occupation. On average, firms in our sample have vacancies that are 54 percent likely to be automatable.[12]

Regarding the main variable of interest, new technology use, we start estimating specifications including a dummy variable for whether the firm adopts at least one of the following new technologies: artificial intelligence, advanced robotics, autonomous transport, advanced manufacturing, 3D-printing, or advanced network services. We further analyze the effect of disaggregated technologies over employment outcomes. The limited number of firms using some technologies (Table 1) constrains us to make the analysis aggregating similar technologies. Following the recent literature (World Economic Forum, 2016; Störmer, et al., 2014), we classify technologies in three groups. First, we group artificial intelligence, advanced robotics and autonomous transport since they are highly related in terms of substituting human labor tasks, particularly in services. Second, we group 3D-printing and advanced manufacturing because they involve manufacturing processes. Finally, advanced services network is more associated with information technologies occupations and those related to the Internet, so we treat them as a separated group.

In addition to firm size, economic sector and number of workers, the set of covariates X includes variables commonly identified as important in the technology adoption literature, that are available in ENHAT and that have not been arguably affected by the new technology adoption. First, following the Schumpeter approach, we include two indicators of market competition (Syverson, 2011): one for the firm's perception about the number of competitors in the market and one for its perception about the demand for its products is elastic to the price set up by the firm or not. If there are many competitors, firms may expect higher demand elasticities due to the existence of close substitutes, which would drive them to adopt new technology to reduce production costs (Majumdar & Venkataraman, 1993).

Following Mairesse and Mohnen (2010), we also include as a demand-pull variable, the expected sales in the following 3 years. To control for experience in the market, we include firm's years of operation (Coad, Segarra, & Teruel, 2016). Moreover, foreign direct investment is another key variable for new technology adoption included. Exposure to international trade facilitates the transfer of knowledge and new technologies (Fatima, 2017). For this, we included a dummy variable indicating whether the firm is owned or controlled by foreign capitals, a dummy for whether the firm exports or not, and a dummy for whether the firm is part of a large corporate group.

[12] Figure A3 in the Appendix shows the distribution of the vacancies' computerization probability for firms using or not new technologies. In contrast to other firms, those using new technologies have vacancies for workers in occupation that are either almost not automatable or highly automatable. Although descriptive, this evidence suggests that new technologies might be complementing high-skilled occupations and substituting middle-skilled ones, as predicted by previous studies (Acemoglu & Autor, 2011; Autor & Dorn, 2013).

Product diversification indicates firms' internal capabilities. Less diversified firms might be so specialized that they have the proper knowledge to use new technologies. However, it is also possible that diversification allows firms to have a lower risk of acquiring new technology or investing in R&D (Garcia-Vega, 2006). To control for this, we include a dummy indicating whether the firm has more than one economic activity or not.

Research and development efforts are crucial for innovation, particularly for new technology adoption. As stated in the seminal work of Crepon, Duguet and Mairesse (1998), the production of innovations depends not only of the decision to make any effort but also the amount invested following a sequential functional form. To account for this, we use a variable indicating whether the firm has a research and development department, or workers exclusively dedicated to these tasks.

Credit and human capital can also constraint firms to adopt new technology. To acquire new technologies, firms need resources for buying the technology and for the associated changes in the production process and non-capital investments (Gomez, & Vargas, 2009). For this, we include a dummy indicating whether the firm has financial obstacles or not. Lastly, the skill levels of the workers might complement the arrival of new technology and increase the probability to adopt new technology (Doms, Dunne, & Troske, 1997). To account for this, we include the percentage of workers that are fully competent.

Our second identification follows Akerman, Gaarder and Mogstad (2015) in using municipality-level information on the availability of broadband Internet as an instrumental variable. We rely on the exogeneity of the broadband availability four years before the survey for identifying the causal effect of new technology adoption on employment outcomes. Specifically, we use the percentage of households accessing the Internet in 2012-2013 in the municipality where a firm is located as a proxy for the broadband availability faced by the firm. For this, we use data from the *Empadronamiento Distrital de Población y Vivienda* 2012-2013 (SISFOH), which is a household census used in Peru for identifying social programs beneficiaries containing information about whether a household has Internet between 2012 and 2013 or not. As Akerman, Gaarder and Mogstad (2015) explain, given the absence of availability rates of broadband Internet to firms, the availability rates to households might serve as an instrument for technology adoption in firms.

5. Results

Overall, we find that new technologies adoption is positively associated with the probability of having at least one vacancy.[13] Firms using at least one of the new technologies are 4 pp more likely to have vacancies than comparable firms not using new technologies. The second and third columns of Table

[13] Table A2 in the Appendix presents the results of a balance test between treated and not treated firms. In particular, it shows a t-test of each covariate used in the propensity score matching before and after the matching. Rows signed by "Unmatched" show the p-value of the t-test for mean differences between firms using and not using new technologies before the kernel matching. In contrast, "Matched" rows present the p-value after the matching. After matching, all covariates are balanced between both groups.

2 show that the effect of the use of new technologies on having new vacancies is driven by having high- and middle-skilled vacancies. Firms using new technologies are 5 pp more likely to have high-skilled (or non-routine cognitive) vacancies and 2 pp more likely to have middle-skilled vacancies than other firms. In contrast, the probability of having low-skilled vacancies is similar between firms using new technologies or not.[14]

Likewise, we find that the use of each one of the three types of technology (AI, robotics and autonomous transport; advanced manufacturing and 3D-printing; and ANS) is associated with a larger demand of high-skilled occupations.

Table 2. New technology adoption effects on labor demand

	Has at least one vacancy	Has at least one high-skilled vacancy	Has at least one middle-skilled vacancy	Has at least one low-skilled vacancy	Probability of computerization
At least one new technology	0.04**	0.05***	0.02**	-0.00	0.02*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
AI or robotics or autonomous transport	0.04	0.07***	0.00	-0.02	-0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Advanced manufacturing and 3D-Print	0.06*	0.07**	0.02	0.00	0.03
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Advanced network services	0.03*	0.04***	0.02**	0.00	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)

Note: Standard errors in parentheses. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table A4 in the Appendix shows that firms using new technologies are more likely to have non-routine cognitive vacancies. In addition, those using ANS are more likely to have routine cognitive vacancies and those using AI, robotics or autonomous transport are less likely to have routine manual vacancies.

Finally, we estimate the effect of new technology adoption on labor demand, using the broadband availability at municipality level as an instrumental variable. We test for weak instrumental variables using Cragg-Donald Wald F-statistic. Table 3 shows that in the specifications for having adopted at least one technology and for ANS, the F-statistics are larger than 71, which are well above the critical value of 10 proposed by Stock, Wright and Yogo (2002) when there is only one endogenous regressor. Moreover, the first-stages show that, as expected, larger availability of Internet in the district where

[14] Similar results are found using nearest neighbor and radius propensity matching methods, indicating that our findings are not sensitive to the matching technique used (Table A3 in the Appendix).

the firm is located increases the likelihood of adopting new technologies. Table 3 also shows that the use of new technologies increases the probability of having at least one high-skilled (or non-routine cognitive) vacancy. These results are similar to the PSM ones. However, in this case, the use of any new technology or ANS increases the chances of having a high-skilled vacancy by 15 pp. Finally, Table A5 in the Appendix shows that firms using new technologies are more likely to have non-routine cognitive vacancies and less likely to have routine manual vacancies.

Table 3. New technology adoption effects on labor demand using IV (2SLS)

	First-stage	Second-stage				
	% household with Internet in the district	Has at least one vacancy	Has at least one high-skilled vacancy	Has at least one middle-skilled vacancy	Has at least one low-skilled vacancy	Probability of computerization
At least one technology	0.28***	0.09	0.15**	0.02	-0.08	0.04
	(0.03)	(0.08)	(0.06)	(0.05)	(0.06)	(0.05)
Cragg-Donald Wald F-statistic	71.48					
AI or robotics or autonomous transport	0.02	1.21	1.90	0.31	-0.99	0.54
	(0.02)	(1.42)	(1.66)	(0.64)	(1.10)	(0.78)
Cragg-Donald Wald F-statistic	1.54					
Advanced manufacturing and 3D-printing	0.01	1.89	2.99	0.48	-1.55	0.84
	(0.02)	(2.73)	(3.64)	(1.08)	(2.19)	(1.41)
Cragg-Donald Wald F-statistic	0.72					
Advanced network services	0.27***	0.10	0.15**	0.02	-0.08	0.04
	(0.03)	(0.08)	(0.06)	(0.05)	(0.06)	(0.05)
Cragg-Donald Wald F-statistic	71.88					

Note: Standard errors in parentheses. *Significant at 10%, **significant at 5%, ***significant at 1%. All regressions control for the following characteristics: number of workers, years of operations, foreign ownership or control, exporting firm, firm has more than one economic activity, firm is a part of a large group, sales will grow, firm has important competitors, demand depends on prices set by the firm, firm has a R&D department or employees, firm has financial obstacles, percentage of competent workers, firm size, and economic sector.

Although our IV proved to be weak in the specifications for the other two types of technology, we can speculate that the results of Table 3 represent a lower bound of the effects of the adoption of these other new technologies. As mentioned above, firms using new technologies different than ANS are even more developed (e.g., larger, more innovative) than firms using ANS only. Thus, it is likely that the use of more sophisticated technologies would lead to a larger demand for higher-skilled workers.

6. Conclusion

Forecasts about the effect of new technologies on labor demand are generally pessimistic, particularly for lower-skilled workers and those whose occupations mainly involve routine tasks. This paper exploits a recent large employer survey 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 adoption of new technologies among formal firms in Peru is still incipient and mainly driven by larger and more productive firms. Also, we find that the adoption of new technologies affects the skills demand. New technologies adoption is associated with a higher demand for high- and middle-skilled workers. However, we find no evidence of an association between the use of new technologies and the demand for low-skilled or computerizable jobs. Moreover, we find that the adoption of new technologies is associated with a higher demand for vacancies with a larger component of non-routine cognitive tasks and a lower demand for vacancies with a larger component of routine manual tasks. These results hold to the use of PSM and IV methods. This evidence suggests that firms in Peru are currently using new technologies and labor mainly as complementary factors.

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 percent of the total number of firms in the country. Including micro formal and informal firms (39 and 59 percent of total firms, respectively), which are presumably more precarious than the small formal firms included in the sample, would furtherly reduce the proportion of firms using new technologies in the country and the estimated average effect on labor demand.

The low rate of technology adoption found among firms in Peru and the country's poor performance in terms of innovation and technology adoption (Cornell University, INSEAD & WIPO, 2018; World Economic Forum, 2018), in comparison to similar countries in the region and elsewhere, represents a burden for the improvement of productivity and growth. To improve productivity, competitiveness and welfare, it is important for Peru to mainly work on three types of public policies. The first one aimed at supporting the development of firms and their adoption of new technologies (e.g., through financial incentives, technical assistance and training). The second one aimed at improving workers' skills, particularly those necessary for continuous learning and the ones that are automatable at a higher cost (e.g., socioemotional and digital skills). The third one aimed at periodically collecting information from firms about skills demand (e.g., enterprise surveys, such as ENHAT) that contribute to the design of pertinent and quality job training programs; and improving the labor intermediation services to gain efficiency in the matching of workers and vacancies. Failures in implementing such policies would compromise Peru's chances of keep developing and growing and would accentuate the existent inequality in the country (i.e., larger demand in better jobs for higher-skilled workers and segregation of lower-skilled workers to low-quality jobs and firms or unemployment).

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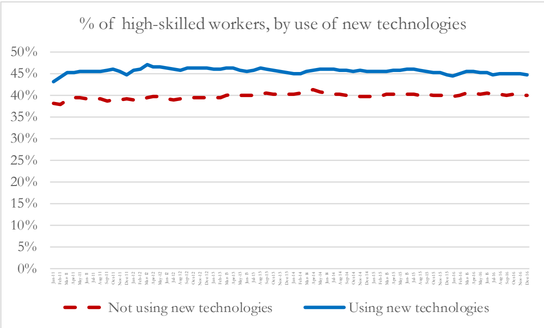
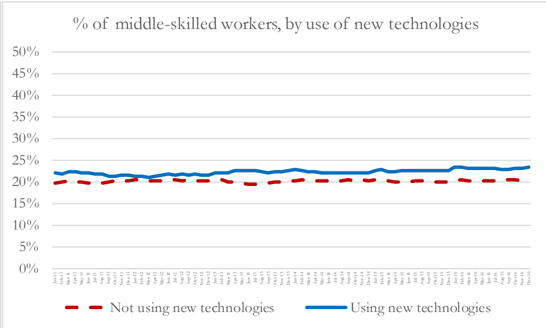
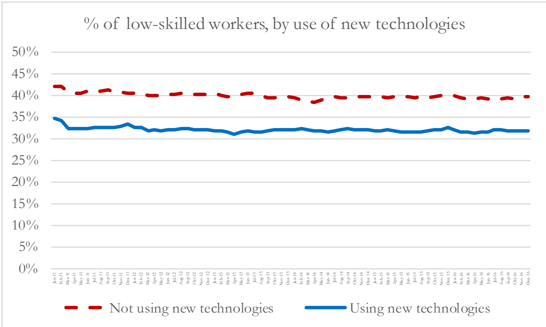
Appendix

Figure A1. Share of workers by skill level and firm's technology adoption (January 2011 – December 2016)







Note: Figures show the monthly average shares of high-, medium-, and low-skilled workers for firms using and not using new technologies that are included in the ENHAT sample. Data comes from an administrative dataset including monthly records of all formal workers and firms in Peru between January 2011 and December 2016.

Figure A2. Common support (post-matching)

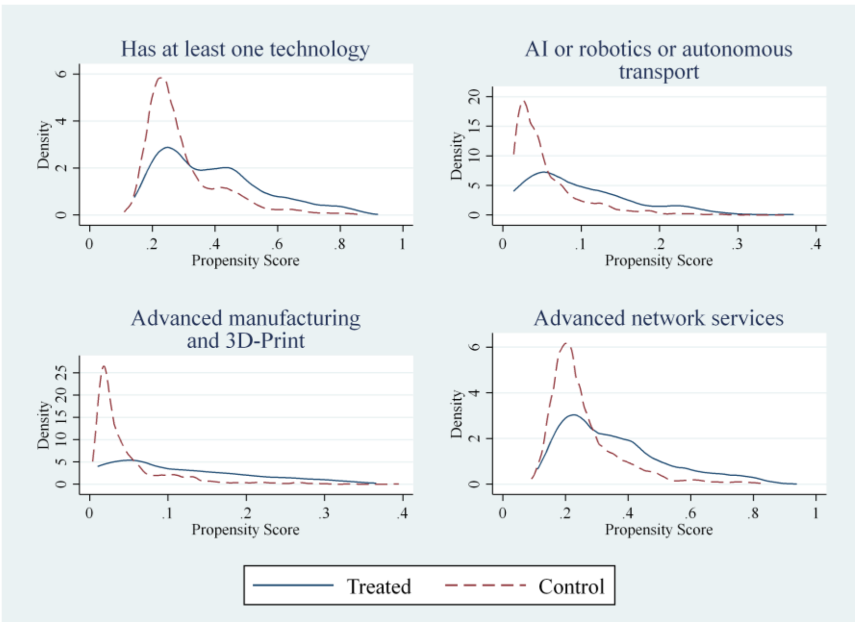
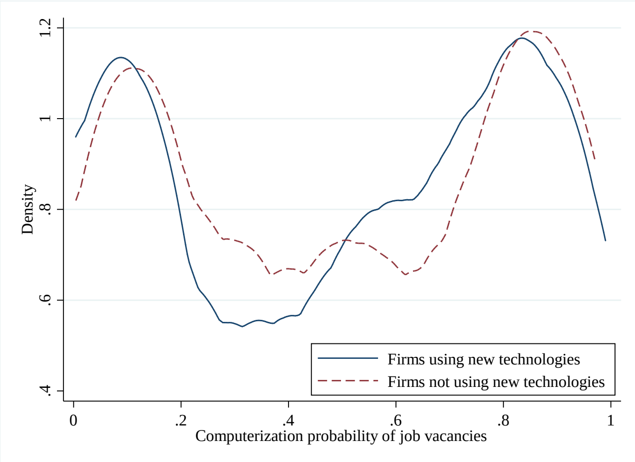


Figure A3. Occupation's Automation Probability and Firms' Technology Adoption (unconditional means)



Note: Calculations using ENHAT sample weights.

Table A1. Firms using technologies and having vacancies, by firm size and economic sector

	Firms with at least one technology		Firm with at least one vacancy	
	%	(SE)	%	(SE)
Firm size				
Large	43.40	(2.01)	19.37	(1.58)
Medium	36.91	(3.62)	11.04	(2.07)
Small	24.60	(0.96)	7.17	(0.58)
Economic sector				
Natural resources	27.92	(3.43)	7.08	(1.66)
Manufacturing	32.50	(2.33)	10.13	(1.47)
Construction	26.30	(3.41)	3.87	(1.35)
Market services	25.61	(1.06)	9.02	(0.68)
Non-market services	31.66	(2.58)	6.52	(1.20)

Note: Calculations using ENHAT sample weights. Standard errors (SE) in parentheses.

Table A2. Balancing test (p-values) between firms adopting or not new technologies

	Matched or unmatched groups	At least one new technology	AI or robotics or autonomous transport	Advanced manufacturing and 3D-Print	Advanced network services
Firm size					
Large	Unmatched	0.00	0.00	0.00	0.00
	Matched	0.80	0.28	0.36	0.69
Medium	Unmatched	0.05	0.78	0.77	0.02
	Matched	0.83	0.99	0.82	0.90

Small	Unmatched	0.00	0.00	0.00	0.00
	Matched	0.71	0.28	0.44	0.76
Economic sector					
Natural resources	Unmatched	0.57	0.01	0.18	0.46
	Matched	0.63	0.60	0.59	0.67
Manufacturing	Unmatched	0.07	0.00	0.00	0.02
	Matched	0.94	0.56	0.59	0.88
Construction	Unmatched	0.80	1.00	0.58	0.85
	Matched	0.81	0.99	0.96	0.94
Market services	Unmatched	0.02	0.00	0.00	0.72
	Matched	0.71	0.37	0.20	0.91
Non-market services	Unmatched	0.06	0.31	0.79	0.02
	Matched	0.89	0.87	0.55	0.98
# of workers (thousands)	Unmatched	0.00	0.02	0.01	0.00
	Matched	0.68	0.79	0.83	0.79
Years of operations (log.)	Unmatched	0.01	0.01	0.02	0.01
	Matched	0.76	0.64	0.98	0.89
Foreign ownership or control=1	Unmatched	0.00	0.00	0.02	0.00
	Matched	0.27	0.68	0.53	0.22
Exporting firm=1	Unmatched	0.00	0.00	0.00	0.06
	Matched	0.83	0.61	0.93	0.75
Firm has more than one economic activity=1	Unmatched	0.03	0.01	0.42	0.04
	Matched	0.54	0.61	0.83	0.81
Firm is a part of a large group=1	Unmatched	0.00	0.00	0.01	0.00
	Matched	0.49	0.55	0.50	0.59
Sales will grow=1	Unmatched	0.01	0.15	0.14	0.02
	Matched	0.68	0.79	0.88	0.81
Has important competitors=1	Unmatched	0.00	0.00	0.03	0.00
	Matched	0.47	0.56	0.90	0.69
Demand depends on prices set by company=1	Unmatched	0.00	0.97	0.05	0.02
	Matched	0.96	0.88	0.62	0.86
R&D department or employees=1	Unmatched	0.00	0.00	0.00	0.00
	Matched	0.43	0.32	0.46	0.42
Has financial obstacles=1	Unmatched	0.30	0.80	0.25	0.29
	Matched	0.82	0.90	0.75	0.89
% competent workers	Unmatched	0.01	0.13	0.57	0.00
	Matched	0.90	0.94	0.90	0.94

Note: "Unmatched" rows show the p-value of the t-test for mean differences between firms using and not using new technologies before the kernel matching. "Matched" rows present the p-value after the matching.

Table A3. New technology adoption and labor demand using alternative propensity score matching algorithms

	Has at least one vacancy	Has at least one high-skilled vacancy	Has at least one middle-skilled vacancy	Has at least one low-skilled vacancy	Probability of computerization
Kernel	0.04**	0.05***	0.02**	-0.00	0.02*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Nearest neighbor	0.05***	0.05***	0.03***	0.01	0.03**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Radius	0.04**	0.05***	0.02**	-0.00	0.02*
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)

Note: Standard errors in parentheses. For the nearest neighbor estimates, we match neighbor firms one-to-one, without replacement. For the radius matching, we set a maximum distance of 0.01.

Table A4. New technology adoption effects on labor demand by task-level

	Has at least one non-routine cognitive vacancy	Has at least one routine cognitive vacancy	Has at least one non-routine manual vacancy	Has at least one routine manual vacancy
At least one technology	0.05***	0.02	-0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
AI or robotics or autonomous transport	0.07***	-0.00	0.00	-0.03**
	(0.03)	(0.02)	(0.01)	(0.01)
Advanced manufacturing and 3D-printing	0.07**	0.01	-0.00	0.02
	(0.03)	(0.02)	(0.01)	(0.02)
Advanced network services	0.04***	0.02*	-0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)

Note: Standard errors in parentheses. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table A5. New technology adoption effects on labor demand, by task level, using IV (2SLS)

	First-stage	Second-stage			
	% household with Internet in the district	Has at least one non-routine cognitive vacancy	Has at least one routine cognitive vacancy	Has at least one non-routine manual vacancy	Has at least one routine manual vacancy
At least one technology	0.28***	0.15**	0.00	0.05	-0.11**
	(0.03)	(0.06)	(0.05)	(0.04)	(0.04)

Cragg-Donald Wald F-statistic	71.48				
AI or robotics or autonomous transport	0.02	1.90	0.02	0.64	-1.42
	(0.02)	(1.66)	(0.72)	(0.69)	(1.25)
Cragg-Donald Wald F-statistic	1.54				
Advanced manufacturing and 3D-printing	0.01	2.99	0.04	1.00	-2.23
	(0.02)	(3.64)	(1.13)	(1.39)	(2.77)
Cragg-Donald Wald F-statistic	0.72				
Advanced network services	0.27***	0.15**	0.00	0.05	-0.11**
	(0.03)	(0.06)	(0.06)	(0.04)	(0.05)
Cragg-Donald Wald F-statistic	71.88				

Note: Standard errors in parentheses. *Significant at 10%, **significant at 5%, ***significant at 1%. All regressions control for the following characteristics: number of workers, years of operations, foreign ownership or control, exporting firm, firm has more than one economic activity, firm is a part of a large group, sales will grow, firm has important competitors, demand depends on prices set by the firm, firm has a R&D department or employees, firm has financial obstacles, percentage of competent workers, firm size, and economic sector.