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Investment in ICT, Productivity, and Labor Demand

The Case of Argentina

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Abstract

This paper explores the impact of the adoption of information and communications technology on firm performance and labor market outcomes using a firm survey from the manufacturing sector in Argentina. The findings are that at the firm level adoption of information and communications technology leads to increases in firm productivity and wages, and that the effects are heterogeneous across firms, being larger for initially high-productivity and high-skill firms. The increase in wages occurs even after controlling for skill composition, implying that there are productivity and rent-sharing mechanisms at play. Further findings show that adoption of information and communications technology is associated with employment turnover as captured by the replacement of workers, elimination of occupations, creation of new occupations, and decrease in the share of unskilled workers, supporting the view that ICT is complementary with skilled labor. At the same time, there is an increase in employment across all skill categories. This result is compatible with positive output effects that drive employment, and with job turnover within the unskilled group.

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Investment in ICT, Productivity, and Labor Demand:

The Case of Argentina[1]

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1. Introduction

In this paper we empirically study the effects of the adoption and use of information and communication technologies (ICT) at the firm level on productivity, wages and employment turnover in the Argentine manufacturing sector.

The question of whether innovation affects productivity and labor outcomes has a long tradition that spans the literature of skilled biased technical change (Katz and Murphy, 1992), the more recent task-based approach of Autor, Levy, and Murnane (2003) and Acemoglu and Autor (2011), and the job polarization arguments of Autor, Katz, and Kearney (2006), and Autor and Dorn (2013), among others. More closely related to digital technologies, Kruger (1993) finds a positive association between the use of computers and wages. More recent studies such as Autor, Levy, and Murnane (2003), Akerman et al (2015) and Michaels, Natraj, and Van Reenen (2014), emphasize that impacts on wages and employment are different by worker or occupation type.

Regarding productivity, ICT adoption is associated with higher productivity outcomes at the country, industry and firm level. In fact, investment in ICT is credited with the increase in labor productivity in the US during the second half of the 1990s and the increasing productivity gap between the US and the EU during that same period. See Draca, Sadun, and Van Reenen (2007) for a literature review of growth accounting and econometric estimation results. The effects of ICT adoption on productivity are found to be largely heterogeneous and to depend on organizational capital and management practices (Bresnahan et al., 2002, Caroli and Van Reenen, 2001, Bloom, Sadun and Van Reenen, 2012).

Using a panel of Argentine manufacturing firms spanning the period 2010-2012 we provide further evidence on the nature of the links between adoption of ICT, productivity, and labor outcomes. We study the effect of ICT adoption on productivity and wages; we explore complementarities with predetermined firm characteristics; and we estimate changes in labor force composition.

During the last decade, the Argentine government has created programs to promote technology adoption and innovation, such as the Argentine Technology Fund (FONTAR), the Trust Fund for the Promotion of the Software Industry (FONSOFT), and the Map of ICT

Innovation in Argentina (MITIC), a web platform that pools information on researchers and universities.[4] In our empirical analysis we use the exogenous exposure to information about these programs, in particular FONTAR, as an instrument for investment in ICT.

We find that at the firm level adoption of ICT leads to increases in firm productivity and wages, and that the effects are heterogeneous across firms, being larger for initially high-productivity and high-skill firms. The increase in wage occurs even after controlling for skill composition, implying that there are productivity and rent-sharing mechanisms at play. We further find that adoption of ICT is associated with employment turnover as captured by the replacement of workers, elimination of occupations, creation of new occupations, and a decrease in the share of unskilled workers, supporting the view that ICT is complementary with skilled labor. At the same time there is an increase in employment across all skill categories. This result is compatible with positive output effects that drive employment and with job turnover within the unskilled group.

The paper is organized as follows. In Section2 we discuss the issues related to ICT and labor outcomes as well as some previous studies for Latin America and Argentina. In Section 3 we describe the data. Section 4 discussed the empirical strategy and Section 5 the results. Section 6 concludes.

2. Digital technology adoption, productivity and labor outcomes

The theoretical effects of technology adoption on labor demand and productivity are in principle ambiguous. For example, process innovation can lead to a substitution of labor for capital, but it can also increase productivity, lower prices, and increase demand, leading therefore to higher employment. Similarly, product innovation usually creates more demand,

[4]The diffusion and use of ICT in Latin America has significantly increased in the last decade. However, compared to other regions, ICT adoption is still relatively low. Grazzi and Jung (2016) show that fixed broadband subscriptions in the US and Western Europe reached 32 connections per 100 people in 2014, while Latin America was far behind with 10 connections per 100 people. With respect to ICT diffusion in enterprises, they show that, overall, ICT diffusion among firms in Latin America appears generally to be higher than in other developing regions. In 2010, almost 85 percent of firms indicated that they had a high-speed internet connection, 90 percent were using email to communicate with clients or suppliers, and 60 percent had their own website. According to the ICT Development Index (IDI), Argentina in particular is ranking at a low 56th place among 155 countries in terms of ICT development, right below Chile and Uruguay and above Brazil (ITU, 2012).

but it can also increase the market power for innovators, raising prices and lowering product demand (Castillo et al, 2011).

The large and persistent difference in measured productivity across producers has been a topic of particular interest for scholars for decades (see Syverson, 2011). Technology adoption has been one of the central factors explaining these differences in productivity among otherwise similar firms. In empirical studies, the basic methodology consists of estimating a firm-level production function to determine whether technology adoption is a significant factor in productivity growth. The meta-analysis by Stiroh (2005) systematically examines the elasticity of productivity with respect to technology for 20 empirical studies published in top journals. Several interesting findings emerge from these studies. First, on average technology is statistically significantly associated with higher firm level productivity. Second, the magnitude of the association between technology and firm productivity is substantial. Third, between different studies, there is huge variation around the average impact of technology on firm productivity.

This evidence supports the view that technology does matter, but the wide variation means that technology alone is not enough to affect productivity. A growing literature focuses on other firm-level features in order to understand this heterogeneity. Caroli and Van Reenen (2001), Bresnahan et al. (2002) and Brynjolfsson and Hitt (2003), among others, show that internal organization and other complementary factors, such as human capital, are important in generating significant returns to technology adoption in production function estimates. Furthermore, Bloom and Van Reenen (2007, 2010) and Bloom, Sadun and Van Reenen (2012) argue that differences in productivity at the firm level could reflect variations in management practices (for example, by enabling companies to use the technology more effectively). These studies find that firms with a higher composition of educated workers tend to have much better management practices, and firms with better management practices tend to be larger, more productive, grow faster, and have higher survival rates. Moreover, Bender et al (2016) show that better managed firms are more likely to recruit higher ability workers and are less likely to lay off the highest skilled workers.

Labor demand and the structure of the workforce might also be affected by the introduction of new technologies. The introduction of new technology and machines can make workers more productive leading to higher wages, but it can also be associated with employment turnover. A large body of empirical studies argues that technology adoption has favored the wage and employment prospects of relatively skilled workers, while simultaneously damaging the wages and employment of the less skilled (see, for example, Autor et al. 1998; Bresnahan et al. 2002; Caroli and Van Reenen 2001). The evidence to date certainly suggests that technological change in the last decades in the US has been skill biased. For instance, Krueger (1993) finds a strong positive correlation between wages and computer use by workers and Doms et al (1997) show that plants that invest relatively more in computing equipment have larger increases in the share of non-production labor. Furthermore, Machin and Van Reenen (1998) provide evidence that skill-biased technical change is an international phenomenon that has had a clear effect of increasing the relative demand for skilled workers.

Another related literature, known as the task-based approach, due to Autor, Levy, and Murnane (2003) argues that technological change substitutes for workers in performing routine tasks, which are more amenable to automatization, and complements workers in executing non-routine tasks such as problem solving, complex communication and information-intensive tasks (see also Acemoglu and Autor, 2011; and Michaels, Natraj, and Van Reenen, 2014). They analyze data at the occupational level and confirm that employment in jobs involving routine tasks has fallen considerably in the US. More recently and for the case of ICT, Akerman et al. (2015) provide compelling causal evidence suggesting that employment and wages of skilled workers increase with broadband internet availability whereas the opposite occurs for unskilled workers. On the firm side, increased availability of broadband internet is associated with an increase in the output elasticity of skilled labor and a decrease in the output elasticity of unskilled labor. They argue that broadband adoption in firms complements skilled workers in executing non-routine abstract tasks, and substitutes for unskilled workers in performing routine tasks.

Finally, another related literature focuses on the phenomenon of job polarization. Autor, Katz, and Kearney (2006) present evidence of rising employment in the highest and lowest paid occupations. Autor and Dorn (2013) hypothesize that polarization stems from the interaction between consumer preferences, which favor variety over specialization, and the falling cost of automating routine, codifiable job tasks. They find that local labor markets that specialized in routine tasks differentially adopted information technology, reallocated low-skill labor into service occupations (employment polarization), experienced earnings growth at the tails of the distribution (wage polarization), and received inflows of skilled labor.

The papers discussed in this section suggest that for our empirical analysis we should expect positive and heterogeneous effects of ICT adoption on labor productivity, and ambiguous effects of ICT adoption on labor demand depending on worker and occupation types.

Focusing on Latin America, Grazzi and Jung (2016) explore the determinants of broadband adoption in a large sample of countries in 2010, and study their relationship with innovation and productivity. They show that using broadband internet is positively and significantly correlated with the probability of product and process innovation in firms. Nonetheless, simple access to ICTs is not enough to foster firm innovation as technology needs to be used adequately to exploit its full potential. The use of broadband also has a positive effect on labor productivity, and this result is robust when controlling for endogeneity.

In Argentina, a series of studies based on different firm-level technology surveys show that during the 2000s, improvements in innovation resulted in an increased demand for labor, productivity and wages. Novick, Rojo, Rotondo and Yoguel (2010) analyze the relationship between innovation activities and employment dynamics during the period 2004-2007. Their results show that the efforts of innovation (training, presence of an R&D team, or IT specialized employees) are positively correlated with firm-level employment growth and workers' earnings, holding age, size, industry sector, and labor productivity constant. In another study, Molina, Rotondo and Yoguel (2013) present descriptive evidence of the importance of ICT on firm productivity. Their results suggest that what matters is how the firm integrates ICT into the organization. While the adoption of ICT cannot explain the change in the productivity of the firms, the effort of innovation (number of workers in R&D teams) is a significant variable. Hence, the adoption of ICT per se does not lead to higher levels of productivity. In a related study, Novick et al (2013) estimate a panel model for the period 2007-2010 finding that wages and employment growth are higher as the ICT structure becomes more complex for firms in the same industry sector, with the same size, age, and productivity level. The authors argue that the results are contrary to the thesis that relates technological unemployment as a consequence of the incorporation of labor-saving technologies, affecting particularly low quality jobs. Moreover, the results are consistent with the perceptions of employers in companies with highly complex ICT adoption processes, who indicated in a set of in-depth interviews that ICT adoption has no obvious impact on staff turnover.

Some public policies related to innovation promotion have also been evaluated through quasi-experimental techniques. López, Reynoso, and Rossi (2010) evaluate the innovation support program FONTAR. They found that beneficiary firms spend more in innovation activities such as R&D and purchase of technology. Castillo et al. (2011) evaluate the impact of the innovation support program PRE on employment and wages. They find that while support for both process and product innovation-related activities leads to increased employment, the support for product innovation has a higher effect on real wages, exporting, and survival probability.

Our paper is also related to a recent surge of articles for Latin American countries studying the effect of different types of innovation on employment growth and the skill composition at the firm-level applying similar methodologies (Alvarez et al., 2011 for Chile; de Elejalde et al., 2011 for Argentina; Monge et al., 2011 for Costa Rica; and Aboal et al., 2011 for Uruguay). The first conclusion from these papers is that while product innovations increase employment, process innovations do not affect it. The results do not change when they account for firm size. A second result is that product innovation increases both skilled and unskilled jobs, with a higher proportion of skilled jobs. However process innovation, in general, has a weakly negative or zero effect on unskilled employment growth. The third result from these papers is that producing technology internally (in-house, or make) has the biggest positive impact on employment, followed by a make-and-buy or buy-only strategy. Finally, some of these papers also conducted interviews with innovation agents. The results indicate that in general innovation does not lead to job losses and that it generates greater demand for a more qualified labor force.

In the same vein, Crespi and Tacsir (2012) present a comparative analysis for these four Latin American countries showing that product innovations are an important source of firm-level employment growth due to demand enlargement. Process innovation accounts for a small share of the changes observed in employment, inducing small or zero displacement effects. The last result can be explained by the absence of productivity gains that would lead to a reduction in employment, or the combined effect of productivity gains (displacement effect), which induce a demand enlargement through market competition (creation effect). Results are similar for small and large firms. They also find some evidence of skill bias of product innovation for high-tech sectors.

Crespi, Tacsir and Vargas (2016) examine the determinants of technological innovation and its impact on firm labor productivity. They use the World Bank Enterprise Survey (WBES) database for 17 Latin American countries in 2010. They find that the decision to invest in innovation (R&D) is strongly correlated with firm size and firm capabilities (human capital) and is significantly and positively affected by public support. They also find that an increase in R&D spending affects positively the probability of innovating. Most of the relationship between expenditure and innovation is through product innovation rather than process innovation. Finally, the effects of innovation on productivity are positive and large. Total factor productivity of innovative firms is 50 % higher than that of non-innovative firms. These results confirm the previous findings by Crespi and Zuñiga (2012) for an earlier period and using micro-data from innovation surveys.

3. Data

Our empirical analysis is based on the *Encuesta Nacional de Dinámica de Empleo e Innovación* (ENDEI, National Survey of Employment Dynamics and Innovation), a firm survey ran in 2013 where manufacturing firms with 10 or more employees provided information about the period 2010-2012 and thus works as a retroactive panel. The ENDEI provides annual information on employment by worker type, average wage, value added, sales, expenditure in R&D and expenditure on different types of innovation. It also provides information on technology use, new technology incorporated during the period of analysis, and relations between technology adoption and the labor force. We match the data from ENDEI with information on informality in employment at the district level, in order to assess whether the relation between ICT and labor demand depends on local labor market institutions.

The sampling frame consisted of 18,900 private manufacturing firms registered in the social security administration. Once the sector and firm size strata were defined, 3,995 firms were selected using a systematic algorithm with equal probability in all strata. The survey is representative at the 2-digit industry level and by firm-size.

Table 1 provides basic descriptive statistics for the year 2012. Firms hire on average 49.5 workers, the average annual wage is 17,065 dollars, and average annual sales are 7,164,000 dollars per year. Unskilled workers account for 87 percent of total employment, skilled workers account for 7 percent, and managers account for 6 percent. These groups earn an average annual wage of 13,984, 22,860, and 37,194 dollars, respectively. The wage gap between skilled and unskilled workers is 40 percent.

In columns (2) to (4) of the same table we show the 5th, 50th and 95th percentile of each variable. Firms are highly heterogeneous, with differences in size of 5,750 and 1,100 percent, measured in sales and employment, between the 95th and 5th percentile. The dispersion of the average wage is comparatively much lower, with a gap of 180 percent. Wage differences between the 95th and 5th percentile are higher for managers, then skilled workers, and finally unskilled workers, at 477, 242 and 183 percent. The decreasing dispersion in wages across skill categories is compatible with two non-mutually exclusive explanations. The first explanation is that within-category variance in skills decreases in the skill category. The second explanation is that skilled workers and especially managers have more negotiating power and their salaries have more correlation with firm performance.

The bottom panel of Table 1 reports descriptive statistics on ICT. During the period 2010-2012, 32 percent of firms report having invested in ICT. The average share of ICT investment in sales is 0.25 percent. Firms report an average of 6.2 workers per computer, and

68 and 43 percent of firms report using software for management of human resources and for management of the production process and sales.

Table 2 explores firm-level predictors of investment in ICT. Each cell shows a separate regression of a dummy variable that indicates whether the firm invested in ICT during 2010-2012 on different firm characteristics in the initial year of data, 2010. Panel A shows that firms are more likely to invest in ICT when they are larger in terms of revenue and are more productive. This is consistent with the idea that larger firms are more likely to be able to cover the fixed costs of investment in technology. Firms are also more likely to invest in ICT when the share of unskilled workers is smaller, suggesting that digital technology and skills are complementary.

To explore the idea that ICT is complementary with firm organization, we also regress ICT adoption on a foreign ownership dummy (that indicates a positive percentage of foreign firm ownership), and a dummy that indicates that the firm is part of a group of enterprises. Results show that foreign firms and firms that are part of a group are 21 and 22 percent more likely to invest in ICT, suggesting that these types of firms have organizational advantages related to ICT adoption (i.e. they are able to replicate organizational practices from firms abroad). Finally, in Panel B we explore the correlation between ICT adoption and characteristics of the CEO or manager. Firms with managers with a college degree are 15 percent more likely to invest in ICT, whereas firms with managers with a graduate degree are 26 percent more likely to invest in ICT. The propensity to invest in ICT is also higher in firms with a young manager (age below 50) and with a manager that has previous experience in a research-related position.

4. Empirical Strategy

The empirical strategy is based on firm-level regressions. We estimate firm fixed effects regressions that seek to establish a link between digital technology adoption, productivity, wages and employment at the firm-level. The regression equation takes the form

$$\Delta y_{is} = \alpha \Delta ICT_{is} + \gamma x_{is} + \delta_s + \varepsilon_{is} \qquad (1)$$

where the dependent variable Δy is defined across different specifications as the change between 2012 and 2010 in productivity, wages, and employment, and ΔICT is a dummy that indicates whether the firm invested in ICT during the same period, thus capturing a change in the stock of ICT capital. Notice that the variable ΔICT takes two possible values, zero or one, indicating whether the stock of ICT capital remained unchanged during the sample period or whether it increased.[5] The specification, and ultimately the available data, does not account for situations in which the stock of ICT decreases. The subindex *i* denotes firms while *s* denotes industry.

The regression is written in first-differences therefore implicitly including firm-fixed effects that are differenced-out. Firm fixed-effects control for time-invariant firm heterogeneity. This is important because unobserved firm characteristics such as the organization of the firms, the quality of their products, their commercial ties, and the professional background of top-tier managers might simultaneously impact the propensity to invest in ICT as well as the left-hand side variables. The effect of investment in ICT on firm performance and employment related outcomes is identified from within firm changes, not from the cross section of heterogeneous firms.

The terms δ_s and x_{is} are industry-level and firm-level trends. Industry level trends are dummies that capture the average increase in the left-hand side variable in the industry between 2012 and 2010. Firm-level trends are defined as firm-size in the initial year of the sample. We define three groups based on employment in 2010: small (fewer than 20 employees), medium (between 20 and 49 employees) and large (50 employees or more), thus capturing the average change between 2012 and 2010 in the left-hand side variables for small, medium and large firms. These trends further control for time-varying unobserved factors that might simultaneously impact the propensity to invest in ICT and the left hand side variables across firms belonging to each industry group and size group.

To further take care of firm-level time-varying unobserved heterogeneity, which is not captured by fixed effects and trends, we estimate regression (1) using instruments, Δz_{is}. The

[5] Recall that as per Table 1, 32 percent of firms report positive investment in ICT during the sample period.

Argentine government implemented a program called FONTAR (Argentine Technological Fund) aimed at improving the competitiveness of private firms by promoting innovation. The program subsidized small investments in technology and digital technology by awarding firms non-refundable funds in the form of grants. Firms go through an application process where their proposals are evaluated by a selection committee.[6]

Participation in the program is not exogenous as funds are assigned following a non-random merit-based process. Our instrument is not based on participation in the program but rather on whether the firm received information on the existence and availability of these programs.[7] Information becomes available to firms by direct public advertising or indirectly through private firms that offer consulting services and aid throughout the application process. To the extent that public and private advertising of the program varied across industries and districts our instrument provides an exogenous shifter of the probability of innovation as it affects the firm-level propensity to participate in the program and to invest in ICT but it does not affect, neither is affected by, the left-hand side variables. Because the effect of information on the probability to invest in ICT might vary by firm characteristics, we interact the firm level access to information (INF) with group of firm-size in the initial year. We expect information to have different impacts on the probability of investment in ICT for small, medium and large firms. Our instrument is thus defined as

$$\Delta z_{is} = INF_{is} \times x_{is} \qquad (2)$$

where INF_{is} is the access to information on the programs and x_{is} are firm-size groups in the initial period defined as before.

Table 3 discusses characteristics of the instrument. In Panel A column (1), 30 percent of firms report having had access to information about the program FONTAR. The access to information varies by firm size (Panel A, columns 2 to 4), with small, medium-sized and large firms reporting having received information in 24, 31 and 39 percent of cases. Panel B shows results of a regression of the access to information dummy on firm characteristics on the initial year of data. The probability of having access to information is increasing in firm size measured

[6] See López, Reynoso, and Rossi (2010) for more details on the program FONTAR.

[7] De Elejalde et al (2011) follow a similar strategy to study the effect of innovation on employment in Argentina for the period 1998-2001.

by employment and sales, increasing in the share of skilled workers, positively related to having a team of R&D workers, negatively related to participation of foreign capital in firm ownership, and not related to the average wage or the stock of computers (measured by an indicator variable for firms that report having an above-average number of computers). Columns 2 to 4 split the samples by firm size (small, medium-sized and large). Once firms are split in size groups, firm characteristics become less relevant. The skill share is correlated with access to information only for medium-sized firms and foreign participation is (negatively) correlated with access to information only for large firms. Having an R&D team is the only variable that correlates with access to information for the three types of firms.

To assess the explanatory power of the instrument, Table 4 reports the first stage regression of investment in ICT during the sample period on access to information interacted with firm size. The two columns correspond to specification without and with firm-specific trends. Results show that our instrument performs well: there is a significant correlation between the instruments and ICT innovation, and the F-statistic is above 10 percent, thus passing the test of Staiger and Stock (1997). Access to information about government funded programs increases the probability of investing in ICT by 12, 11 and 9 percent for small, medium and large firms.[8]

5. Results

In this section we discuss the estimation results. We start by discussing the impact of investment in ICT on firm performance, given by labor productivity and by revenue. We then turn to average wages and wages by worker type. In the last subsection we discuss employment turnover.

[8]The variable ΔICT is a dummy variable and does not capture the intensity of the investment in ICT or the intensity of the change in the stock of ICT. We have also experimented with the value of expenditure in ICT divided by sales. We find that, unlike in the ICT dummy case, the information instrument does not have strong predictive power to explain ICT intensity. For completeness we have included results from regressions based on ICT investment in the Appendix.

Firm Performance

In Table 5 we study the effect of the adoption of ICT on firm performance. In Panel A we estimate equation (1) with the change in the log of labor productivity on the left-hand side and investment in ICT on the right. We focus on labor productivity as the firm-survey does not contain information on the capital stock and we cannot compute total factor productivity. The first column reports the fixed effects estimate. As expected, ICT increases the productivity of workers. Investment in ICT causes labor productivity to increase by 7.4 percent. This result is robust to adding firm-specific trends in column (2), which shows an increase in productivity of 7 percent. Columns (3) and (4) report results using fixed effects and instruments (column 4 controls for firm specific trends). As discussed in the previous section, the instruments are the availability of information interacted with firm-size group. When ICT is instrumented, its estimated effects on labor productivity are of 21 and 20 percent. For completeness we also study the effect of ICT on firm size, as increases in productivity should be reflected in increases in sales. Panel B reports the effect of ICT on total firm revenue. The estimated effects when using instruments are of 165 and 159 percent.

The effects of ICT need not be equal across firms. The increase in labor productivity depends on how well the firm employees interact with the new stock of ICT which in turn depend on worker and firm characteristics. To study heterogeneous effects across firms, our estimating regression is

$$\Delta y_{is} = \alpha_0 \Delta ICT_{is} + \alpha_1 \Delta ICT_{is} \times \varphi_{is0} + \gamma x_{is0} + \delta_s + \varepsilon_{is}. \qquad (3)$$

The variable φ_{is0} represents firm type defined as firm characteristics in the initial year of data. The coefficients of interest are α_0 and α_1. The coefficient α_0 captures the average effect of ICT whereas the coefficient α_1 captures effects of ICT that vary by firm type. Results are reported in Table 6.

We start by studying heterogeneous effects according to whether firms are initially of high-productivity type. High productivity is defined as labor productivity above the industry median. Results show that investment in ICT by high-productivity firms causes an additional increase of 23 percent (column 4) relative to low-productivity firms. In fact, the effect of ICT on productivity for low-productivity firms is not statistically significant. The implication of this result is that investment in ICT increases the productivity gap between low and high productivity firms. We also find that the effect of ICT on productivity is 12 and 13 percent larger for firms with a large share of skilled workers (above the 75th percentile in the industry) and with high average wages (above the industry median). Average wages are a proxy for average skills as well. These results are related to the literature that argues that differences in productivity at the firm level could reflect variations in management practices (Bloom and Van Reenen, 2007). Bender, Bloom et al (2016) find that firms with a more able workforce, and in particular more able workers in the top quartile of the skill distribution, tend to have better management practices and higher productivity.

We further explore whether the effect of ICT on productivity depends on the existing stock of ICT. The existing stock of ICT could be directly complementary with the new investment. In addition, in the presence of an already high-ICT environment, workers are more likely to be trained to interact with the new technologies thus reducing fixed costs and training time. The existing stock of ICT is proxied in two separate regressions by a dummy indicating whether the firm performs operations through the internet, and a dummy indicating whether the firm has at least one computer per three employees. Results for the internet dummy are not significant whereas firms that have a large number of computers see their labor productivity increased by 15 percent more relative to firms that have a smaller number of computers, as a result of new ICT investment.

Finally, we further pursue the management-practices point of Bloom and Van Reenen (2007) and Bloom, Sadun and Van Reenen (2012) by looking at heterogeneous effects of ICT for firms with foreign ownership, firms that belong to a group of enterprises, and firms with a manager that has previous job experience in research activities. The first two variables capture whether firms are able to “import” management practices from other firms through ownership linkages, whether the manager variable captures externalities that work through previous jobs. None of these variables are significant and we thus do not find support for these ideas in our dataset. Nevertheless, we interpret these results with caution as we do not directly measure management practices.

Summing up, we find that the extent to which investment in ICT results in higher labor productivity depends on the initial level of productivity, of skill labor, and the existing stock of ICT. These results highlight the idea that ICT is complementary to high skill labor and previous investment in digital technology.

Wages

To the extent that investment in ICT results in higher labor productivity, we should observe an increase in wages. The increase in wages could work directly, because of the increase in the marginal product of labor. It could also work indirectly, through an increase in profits of the firm and rent-sharing with the workers. Furthermore, if ICT is complementary with skills, an increase in wages could be due to an increase in the share of skilled workers (a result that we confirm in the next subsection).

In Table 7 we estimate equation (1) with the change in firm-level log average wage on the left-hand side. Results from columns (1) and (2) show a small (and in the second case non-significant) relationship between ICT adoption and the change in wages. When we estimate the regression using instruments (columns 3 and 4), we find that investment in ICT results in an average increase in wages of 8 and 7.6 points. In the second regression specification we control for the share of skilled workers. This regression aims to control for compositional effects. Even after controlling for the change in skills, wages are found to increase by 7.8 and 7.6 percent, favoring the explanation that increases in wages work through productivity or rent-sharing and not merely by composition.

In the last two panels of Table 7 we further find that the effect of ICT on wages is higher for high-productivity and high-skill firms, as defined in Table 6. This result is consistent with the complementarity findings of Table 6, where ICT results in higher labor productivity, and thus higher marginal product of labor and higher profits, for certain types of firms. It is also possible as an additional explanation that workers in high-productivity firms, and high skill workers, have more bargaining power and are able to participate more in firm profits.

To provide more information on the relationship between investment in ICT and wages, and to further isolate results from compositional effects, in Table 8 we estimate separate models for the change in wages by worker type. We estimate the effect of ICT on the wage of managers (columns 1 and 2), skilled workers (columns 3 and 4), and unskilled workers (columns 5 and 6).[9] We find that investment in ICT results in increases in wages for all three categories of workers. The increases are of 28 percent for managers, 12 percent for skilled workers, and 11 percent for unskilled workers. The effects are larger for high-productivity firms and for high-skill firms in all three categories.

One salient feature of Table 8 is that the increase in wages is very close for skilled and unskilled workers whereas it is twice as high for managers. Increases in productivity work mostly through the increase in efficiency, speed and accuracy derived from automatization of tasks. Tasks performed by managers are the least susceptible to automatization, quite the contrary, and the marginal product of managers therefore need not increase more than the marginal product of other workers. This result thus suggests that there could be a rent-sharing mechanism in place, where the wages of managers are more linked to firm-performance that the wages of other employees, skilled and unskilled.

In Tables 9 and 10 we proceed to study the change in labor productivity as a channel linking digital technology adoption and higher wages. The estimating equation is

$$\Delta w_{is} = \alpha \Delta PROD_{is} + \gamma x_{is0} + \delta_s + \varepsilon_{is} \tag{4}$$

where Δw_{is} is the change in the average wage, overall and by worker type across different specifications, as in Tables 7 and 8, and $\Delta PROD_{is}$ is the change in labor productivity. We instrument the change in productivity with the same instrument as in the previous regressions: the exposure to information on government programs. While exposure to information does not affect productivity directly, it works through ICT as shown in Tables 5 and 6. Estimating regression (4) by 2SLS using the exposure to information as an instrument, is equivalent to a three step procedure in which ICT is first regressed on information, productivity is then regressed on predicted ICT, and wages are regressed on predicted productivity.

Because of the indirect relationship between the instrument and productivity, the results in Tables 9 and 10 are more imprecisely estimated than in previous regressions. Coefficients are positive and large but several confidence intervals are large as well. Results are

[9]We keep the specifications with firm-specific trends, analogous to columns 2 and 4 in Table 7.

larger and statistically stronger for high-productivity firms in both Table 9 and Table 10. An increase of 10 percent in labor productivity results in an increase of 2.4 percent in wages in high-productivity firms (Table 9), and in increases of 6.7, 2.2, and 3.1 percent for managers, skilled workers and unskilled workers, also in high-productivity firms (Table 10).

Lastly, in Table 11 we study the change in the wage gap between skilled and unskilled workers. Managers are included in the skilled group. The wage gap increases by 6.1 percentage points. We do not find compelling evidence that firms that were initially more productive or had a higher initial share of skilled workers responded differently.

Employment turnover

In the final part of the analysis we shift the attention to the relationship between employment turnover and investment in ICT. Due to routinization of tasks, ICT is likely to replace some workers or occupations, whereas it is likely to complement others.

Table 12 presents preliminary descriptive evidence regarding occupational changes for the group of firms that report having gone through some form of innovation during the period of analysis.[10] Each cell corresponds to a separate regression where the dependent variables are three indicators of job turnover indicating: whether workers were replaced (columns 1 and 2), whether occupations were eliminated (columns 3 and 4), and whether occupations were created (columns 5 and 6). In the first panel we show raw averages of each indicator. Firms that invest in ICT report that in 5.6 percent of cases the innovation led to replacing workers, in 10 percent of firms it led to replacing occupations, and in 31.8 percent of cases it led to creating new occupations. In the following horizontal panels we look at employment turnover by firm characteristics. These regressions are simple correlations. High productivity is not a predictor of employment turnover. There is mild evidence suggesting that firms with a higher skill share are more likely to replace occupations and that firms with a high computer-worker ratio are more likely to replace workers. The most relevant firm characteristic is the dummy that indicates operations through the internet, which is strongly associated with all three forms of

[10] Information is not available for firms that did not go through investment in ICT during the sample period. In fact, the survey question refers to changes in employment that occurred *as a result* of ICT.

employment turnover: replacing workers, eliminating occupations, and creating new occupations.

In Table 13 we directly look at the change in employment composition by estimating equation (1) with the share of unskilled workers in total firm employment on the left-hand side. To the extent that ICT is a complement of skilled labor, we should observe a decrease in the share of unskilled workers. The regression thus tests whether ICT is a higher complement of skilled or unskilled labor. Results show that ICT investment leads to a decrease in the share of unskilled workers of 3.8 percentage points. Effects do not appear to be heterogeneous across firm characteristics with the exception of firms that operate through the internet. In firms with no internet operations the share of unskilled workers does not fall. This variable is a proxy for existing digital technology or existing management and work practices related to digital technology.

Employment turnover is affected by labor regulations. In particular, employment turnover is more likely to occur in flexible environments whereas replacing workers becomes more costly when there are large firing and hiring costs. In Argentina firing costs are high but labor informality is pervasive. Informal employment flies under the radar of labor regulations and informal workers are not usually offered severance payments when displaced. In Table 14 we look at the relation between employment turnover due to ICT and local labor market institutions. We interact ICT adoption with a dummy that is equal to one for firms in local labor markets with high levels of employment informality (defined as districts where the share of workers that do not pay social security contributions is above the mean across districts). We find that the decrease in the share of unskilled workers after investment in ICT is 1.5 percentage points higher for firms in districts with high levels of informality and therefore with lower labor adjustment costs.

Having established that investment in ICT results in job turnover and a decrease in the share of unskilled workers, thus appearing to be negatively related to unskilled employment, it is important to recall that investment in ICT is also productivity and revenue enhancing (Tables 5 and 6). The expansion in output works in the direction of increasing employment in all labor categories. The correlation between ICT and unskilled employment is therefore ruled by two opposing effects (as described in Brambilla, 2017): a negative substitution effect given by the complementarity between ICT and skilled labor, and a positive output effect given by the increase in firm size. In Tables 15 and 16 we estimate the effects of ICT on employment.

In Table 15 we show estimates of the effect of ICT on total firm employment. The first panel, column 4, shows that firm employment increases by 60 percent due to investing in ICT, on average. In the last panel we split firms into two groups: high and low output growth, depending on whether growth in revenue during the sample is above or below the median. The increase in employment is 50 percent for low growth firms and 72 percent for high growth firms. This result is compatible with the idea that there is an output effect where the increase in employment is driven by the increase in output.

Table 16 reports estimates for changes in employment by worker type. Employment increases by 20, 33 and 27 percent for managers, skilled workers, and unskilled workers. Whereas Tables 12 and 13 document that there is a decrease in the share of unskilled workers, Table 16 shows that total employment increases across all worker types, including unskilled workers, and that therefore the positive output effect is larger than the negative substitution effect. In the last panel, the increase in employment is between 8 and 10 percent larger for high growth firms across all worker types.

Tables 15 and 16 report increases in employment, whereas results in previous tables report losses of some jobs. In particular, Table 12 reports job turnover and the elimination of occupations, and Table 14 reports that the substitution effect that works against unskilled workers is higher in districts with high levels of informality, which suggests that on average unskilled workers are indeed being fired. These two seemingly opposing results are compatible with a scenario in which there is job turnover within skill categories or at least within the unskilled group. In particular, unskilled employment could decrease for repetitive unskilled occupations due to the negative substitution for technology effect, and could simultaneously increase for other unskilled workers as a result of the positive increase in output effect, with the net effect being on average an increase in unskilled employment.

6. Conclusion

We have explored the causal impact of ICT adoption on firm performance and labor market outcomes. We find that at the firm level adoption of ICT leads to increases in firm productivity and wages, and that the effects are heterogeneous across firms, being larger for initially high-productivity and high-skill firms. The increase in wage occurs even after controlling for skill composition, implying that there are productivity and rent sharing mechanisms in play. The increase in wages is twice as high for managers compared to other skilled and unskilled workers.

We further find that adoption of ICT is associated with employment turnover as captured by the replacement of workers, elimination of occupations and creation of new occupations. There is a decrease in the participation of unskilled workers, supporting the view that ICT is complementary with skilled labor. The drop in the participation of unskilled workers is higher in districts where labor adjustment costs are lower. At the same time, the adoption of ICT leads to an increase in the number of workers across all categories. This effect is largest for skilled workers and for firms with high output growth during the sample period. The finding that some unskilled jobs are lost together with the finding that unskilled employment increases points towards job turnover within the unskilled group.

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TABLE 1. ENDEI survey

	Mean	5th percentile	50th percentile	95th percentile
Number of firms	3691			
Sales and employment				
Sales (thousands of USD)	7163.8	226.3	1508.7	13241.5
Number of workers	49.5	9	23	108
Share managers	0.057	0	0.038	0.14
Share skilled	0.067	0	0.053	0.17
Share unskilled	0.876	0.67	0.89	1
Average annual wage (USD)	17065.3	9236.8	15456.0	25917.0
Managers	37193.8	12195.1	29268.3	70429.3
Skilled workers	22859.5	10731.7	19512.2	36707.3
Unskilled workers	13984.2	7317.1	12829.3	20731.7
Gap skilled-unskilled	0.40	0.02	0.35	0.79
Information and communication technologies				
Investment in ICT	0.32	0	0	1
Investment in ICT/Sales	0.0025	0.0002	0.0016	0.0052
Workers per computer	6.2	1.3	4.4	12.2
HHRR management system	0.68			
Production management system	0.43			

Own calculations based on ENDEI (Encuesta Nacional de Dinámica de Empleo e Innovación), 2010-2012.

TABLE 2. ICT predictors

Panel A: Firm characteristics	Revenue	Labor Productivity	Share Unskilled	Foreign Ownership	Part of Group
ICT	0.088***	0.051***	-0.58***	0.21***	0.22***
	(0.0047)	(0.0084)	(0.10)	(0.029)	(0.025)
Observations	3,523	3,434	3,584	3,656	3,691
Panel B: Characteristics of manager	College Degree	Graduate Degree	Less than 50 years old	Previous Experience	
ICT	0.15***	0.26***	0.065***	0.13***	
	(0.016)	(0.029)	(0.016)	(0.023)	
Observations	3,691	3,691	3,691	3,675	

Correlation between investment in ICT and characteristics of firm and manager at the beginning of the sample period. Industry controls. Robust standard errors.

TABLE 3. Characteristics of the instrument

	Information			
	All firms	Small firms	Medium-sized firms	Large firms
	(1)	(2)	(3)	(4)
Panel A				
Mean	0.30	0.24	0.31	0.39
Panel B: regressions				
Mid-size	0.057***	--	--	--
	(0.020)			
Large	0.059*	--	--	--
	(0.034)			
Log sales	0.013*	0.016	0.015	0.0041
	(0.0075)	(0.011)	(0.014)	(0.016)
Foreign participation	-0.092***	0.12	-0.0045	-0.17***
	(0.033)	(0.089)	(0.059)	(0.047)
Log wage	0.016	0.036	-0.0010	0.0047
	(0.018)	(0.025)	(0.030)	(0.044)
Skill share	0.15***	0.066	0.36***	0.086
	(0.051)	(0.074)	(0.095)	(0.10)
R&D team	0.19***	0.14**	0.19***	0.23***
	(0.028)	(0.063)	(0.047)	(0.043)
Computers	-0.087	-0.051	-0.086	-0.11
	(0.076)	(0.11)	(0.13)	(0.18)
Observations	3,235	1,316	1,210	709

Panel A shows the percentage of firms that report having had access to information about FONTAR program. Panel B regresses a dummy variable of information about FONTAR program on initial-year firm characteristics.

TABLE 4. First stage.

	Δ ICT	
	(1)	(2)
Information * Small	0.13***	0.12***
	(0.029)	(0.029)
Information * Med-size	0.11***	0.11***
	(0.030)	(0.030)
Information * Large	0.097***	0.090**
	(0.036)	(0.036)
Observations	3,434	3,419
F-stat	13	12.2
Industry effects	Yes	Yes
Trends		Yes

First stage regression of 2SLS. Dependent variable: dummy indicating whether firm invested in ICT during sample period. Instrument: dummy indicating whether firm was exposed to information on government program to finance ICT investment interacted with firm-size indicators at the beginning of the sample period.

TABLE 5. Firm performance after investment in ICT

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Panel A: Δ Labor Productivity				
Δ ICT	0.074***	0.070***	0.21***	0.20***
	(0.019)	(0.019)	(0.064)	(0.064)
Observations	3,391	3,382	3,391	3,382
Panel B: Δ Log Revenue				
Δ ICT	0.16***	0.089***	1.65***	1.59***
	(0.025)	(0.019)	(0.38)	(0.40)
Observations	3,517	3,477	3,517	3,477
Industry effects	Yes	Yes	Yes	Yes
Trends		Yes		Yes

Dependent variable: change in log value added per worker (Panel A) and change in log revenue (Panel B). Regressor: variable indicating whether firm invested in ICT during the sample period. Instrument: dummy indicating whether firm was exposed to information on government program to finance ICT investment interacted with firm-size indicators at the beginning of the sample period. Columns (2) and (4) control for firm specific trends. Robust standard errors in parenthesis.

TABLE 6. Labor productivity and complementarities of ICT

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	0.029	0.032	0.065	0.052
	(0.030)	(0.031)	(0.091)	(0.089)
Δ ICT * High Productivity	0.083**	0.070*	0.23**	0.23**
	(0.039)	(0.039)	(0.096)	(0.096)
Δ ICT	0.068***	0.063***	0.17***	0.16**
	(0.021)	(0.021)	(0.065)	(0.065)
Δ ICT * Skills	0.024	0.025	0.11**	0.12**
	(0.032)	(0.032)	(0.053)	(0.052)
Δ ICT	0.010	0.018	0.091	0.074
	(0.025)	(0.024)	(0.091)	(0.090)
Δ ICT * Wage	0.10***	0.088***	0.12**	0.13**
	(0.030)	(0.031)	(0.062)	(0.060)
Δ ICT	0.040	0.033	0.10	0.066
	(0.13)	-0.13	(0.33)	(0.32)
Δ ICT * Internet	0.034	0.037	0.10	0.13
	(0.13)	(0.13)	(0.32)	(0.32)
Δ ICT	0.059**	0.041*	0.17**	0.14*
	(0.024)	(0.024)	(0.075)	(0.074)
Δ ICT * Computers	0.033	0.065**	0.098*	0.15***
	(0.030)	(0.030)	(0.053)	(0.053)
Δ ICT	0.062***	0.062***	0.19***	0.18**
	(0.019)	(0.020)	(0.069)	(0.069)
Δ ICT * Foreign	0.061	0.032	0.044	0.039
	(0.052)	(0.051)	(0.068)	(0.067)
Δ ICT	0.067***	0.070***	0.20***	0.21***
	(0.020)	(0.020)	(0.073)	(0.073)
Δ ICT * Group	0.041	0.00034	0.012	-0.010
	(0.042)	(0.043)	(0.060)	(0.060)
Δ ICT	0.077***	0.072***	0.23***	0.22***
	(0.021)	(0.021)	(0.067)	(0.067)
Δ ICT * Exp Manager	-0.023	-0.024	-0.049	-0.044
	(0.029)	(0.029)	(0.052)	(0.051)
Observations	3,391	3,382	3,391	3,382

Dependent variable: change in log value added per worker. Regressors: ICT investment dummy, and ICT investment dummy interacted with firm-level indicator variables that are equal to one when: firm labor productivity is above the median, firm share of skilled labor is above the 75th percentile, firm average wage is above the median, firm has internet connection, there are less than 3 employees per computer, firm is of foreign ownership, firm belongs to a group, firm manager has experience in research. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 7. Average wage

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	0.014*	0.011	0.080***	0.076***
	(0.0072)	(0.0074)	(0.027)	(0.026)
Δ ICT	0.013*	0.010	0.078***	0.076***
	(0.0072)	(0.0074)	(0.026)	(0.026)
Δ Skills	0.29***	0.16**	0.28***	0.12*
	(0.071)	(0.065)	(0.072)	(0.066)
Δ ICT	-0.0013	-0.0021	0.043	0.041
	(0.0098)	(0.0098)	(0.030)	(0.030)
Δ ICT * High Productivity	0.025**	0.022**	0.039**	0.040**
	(0.011)	(0.011)	(0.019)	(0.019)
Δ Skills	0.29***	0.16**	0.28***	0.13**
	(0.071)	(0.065)	(0.072)	(0.066)
Δ ICT	0.0044	0.0016	0.060**	0.057**
	(0.0078)	(0.0079)	(0.026)	(0.026)
Δ ICT * Skills	0.034***	0.035***	0.060***	0.059***
	(0.011)	(0.011)	(0.016)	(0.016)
Δ Skills	0.30***	0.16**	0.29***	0.13**
	(0.071)	(0.065)	(0.072)	(0.066)
Observations	3,329	3,318	3,329	3,318

Dependent variable: change in log average wage. Regressors: ICT investment dummy, ICT investment dummy interacted with firm-level indicator variables defined as in Table 5, and change in share of skilled workers. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 8. Wage by worker type. ICT intensity

	Managers		Skilled Workers		Unskilled Workers	
	FE	FE-2SLS	FE	FE-2SLS	FE	FE-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ICT	0.013	0.28***	-0.0031	0.12***	0.016**	0.11***
	(0.012)	(0.054)	(0.0085)	(0.037)	(0.0072)	(0.027)
Δ ICT	-0.00032	0.22***	-0.016	0.080**	-0.0069	0.046
	(0.016)	(0.060)	(0.011)	(0.039)	(0.0095)	(0.030)
Δ ICT * Prod	0.022	0.061**	0.021*	0.047**	0.041***	0.080***
	(0.016)	(0.031)	(0.012)	(0.020)	(0.011)	(0.018)
Δ ICT	0.0030	0.24***	-0.011	0.11***	0.0074	0.086***
	(0.012)	(0.053)	(0.0090)	(0.037)	(0.0078)	(0.026)
Δ ICT * Skills	0.035**	0.074**	0.031**	0.060***	0.035***	0.074***
	(0.017)	(0.029)	(0.012)	(0.020)	(0.011)	(0.017)
Observations	2,246	2,246	2,333	2,333	3,212	3,212

Dependent variable: change in log average wage of managers (columns 1 and 2), skilled workers (columns 3 and 4) and unskilled workers (columns 5 and 6). Regressors: ICT investment dummy, and ICT investment dummy interacted with firm-level indicator variables defined as in Table 5. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 9. Average wage. Productivity channel

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
∆ Productivity	0.041***	0.034***	0.53*	0.50
	(0.0096)	(0.0085)	(0.30)	(0.32)
∆ Productivity	0.037***	0.032***	0.11*	0.10
	(0.011)	(0.0098)	(0.065)	(0.072)
∆ Prod * High Prod	0.016	0.011	0.14**	0.14**
	(0.014)	(0.013)	(0.059)	(0.061)
∆ Productivity	0.035***	0.030***	0.34*	0.31*
	(0.0088)	(0.0085)	(0.18)	(0.18)
∆ Prod * Skills	0.017	0.013	0.043	0.041
	(0.018)	(0.016)	(0.030)	(0.028)
Observations	3,160	3,151	3,160	3,151

Dependent variable: change in log average wage. Regressors: change in labor productivity, and change in labor productivity interacted with firm-level indicator variables defined as in Table 5. Instruments as in Table 3. Robust standard errors in parenthesis.

TABLE 10. Wage by worker type. Productivity channel

	Managers		Skilled Workers		Unskilled Workers	
	FE	FE-2SLS	FE	FE-2SLS	FE	FE-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Productivity	0.040***	0.58*	0.024***	0.53	0.020**	0.58*
	(0.0099)	(0.34)	(0.0089)	(0.43)	(0.0086)	(0.32)
Δ Productivity	0.022**	0.31**	0.014	0.070	0.012	0.11
	(0.010)	(0.14)	(0.0095)	(0.070)	(0.0099)	(0.072)
Δ Prod * High Prod	0.064***	0.36***	0.031**	0.15**	0.031**	0.21***
	(0.018)	(0.11)	(0.015)	(0.060)	(0.013)	(0.058)
Δ Productivity	0.036***	0.40*	0.020**	0.12	0.013	0.32**
	(0.011)	(0.21)	(0.0087)	(0.15)	(0.0083)	(0.16)
Δ Prod * Skills	0.011	0.047	0.014	0.047*	0.022	0.044
	(0.017)	(0.043)	(0.016)	(0.025)	(0.017)	(0.030)
Observations	2,141	2,141	2,221	2,221	3,055	3,055

Dependent variable: change in log average wage of managers (columns 1 and 2), skilled workers (columns 3 and 4) and unskilled workers (columns 5 and 6). Regressors: change in labor productivity, and change in labor productivity interacted with firm-level indicator variables defined as in Table 5. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 11. Wage gap skilled-unskilled

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	-0.0039	-0.015	0.059*	0.061**
	(0.0086)	(0.0090)	(0.031)	(0.031)
Δ ICT	-0.0055	-0.015	0.053	0.058
	(0.011)	(0.011)	(0.037)	(0.037)
Δ ICT * High Productivity	0.0026	0.00038	0.0051	0.0023
	(0.012)	(0.012)	(0.019)	(0.019)
Δ ICT	-0.0071	-0.016*	0.052	0.055*
	(0.0092)	(0.0093)	(0.032)	(0.031)
Δ ICT * Skills	0.012	0.0072	0.021	0.018
	(0.014)	(0.014)	(0.018)	(0.018)
Observations	2,294	2,284	2,294	2,284

Dependent variable: change in log average wage of skilled workers relative to unskilled workers. Regressors: ICT investment dummy, and ICT investment dummy interacted with firm-level indicator variables defined as in Table 5. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 12. Indicators of job turnover after investment in ICT

	Replaced Workers		Eliminated Occupations		Created Occupations	
	(1)	(2)	(3)	(4)	(5)	(6)
Probability	0.0562***		0.101***		0.318***	
(no controls)	(0.00563)		(0.00728)		(0.0111)	
Observations	1,672		1,719		1,750	
High Productivity	0.0014	0.00089	-0.015	-0.013	-0.039	-0.041*
	(0.012)	(0.012)	(0.016)	(0.016)	(0.024)	(0.024)
Skills	0.0018	0.00057	0.032*	0.033*	-0.015	-0.016
	(0.013)	(0.013)	(0.018)	(0.018)	(0.026)	(0.026)
Internet	0.044***	0.034**	0.11***	0.13***	0.22**	0.19*
	(0.012)	(0.017)	(0.020)	(0.031)	(0.097)	(0.099)
Computers	0.027**	0.024*	-0.027*	-0.020	0.028	0.019
	(0.012)	(0.012)	(0.016)	(0.017)	(0.024)	(0.025)
Observations	1,629	1,626	1,673	1,670	1,706	1,703
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Trends		Yes		Yes		Yes

Dependent variable: dummy indicating whether workers were replaced (columns 1 and 2), whether occupations were eliminated (columns 3 and 4), and whether occupations were created (columns 5 and 6). Regressors: raw average (first panel), and firm-level indicator variables defined as in Table 5. All regressions in first differences. Robust standard errors in parenthesis.

TABLE 13. Job turnover. Share of unskilled workers

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	-0.0011	-0.0056***	-0.0011	-0.038**
	(0.0017)	(0.0016)	(0.019)	(0.018)
Δ ICT	0.00018	-0.0046***	-0.0052	-0.035*
	(0.0016)	(0.0016)	(0.021)	(0.018)
Δ ICT * High Productivity	-0.0022	-0.0019	-0.00035	0.000036
	(0.0021)	(0.0020)	(0.0049)	(0.0043)
Δ ICT	-0.0013	-0.0056***	-0.0052	-0.040**
	(0.0018)	(0.0016)	(0.018)	(0.017)
Δ ICT * Skills	0.00098	-0.00014	-0.0038	-0.0061
	(0.0028)	(0.0026)	(0.0054)	(0.0048)
Δ ICT	0.010**	0.0079	0.029	0.0096
	(0.0039)	(0.0050)	(0.018)	(0.016)
Δ ICT * Internet	-0.011***	-0.014***	-0.021**	-0.042***
	(0.0039)	(0.0050)	(0.0098)	(0.0084)
Δ ICT	-0.00085	-0.0028**	-0.011	-0.049**
	(0.0016)	(0.0014)	(0.020)	(0.020)
Δ ICT * Computers	-0.00045	-0.0064**	0.0019	0.0024
	(0.0024)	(0.0027)	(0.0060)	(0.0057)
Observations	3,566	3,564	3,566	3,564

Dependent variable: change in the share of unskilled workers. Regressors: ICT investment dummy, ICT investment dummy interacted with firm-level indicator variables defined as in Table 5. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 14. Job turnover. Share of unskilled workers

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	0.0077**	0.0042	0.011	-0.027
	(0.0032)	(0.0036)	(0.018)	(0.018)
Δ ICT * Informality	-0.0091***	-0.010***	-0.017***	-0.015**
	(0.0032)	(0.0037)	(0.0066)	(0.0071)
Observations	3,566	3,564	3,566	3,564

Dependent variable: change in the share of unskilled workers. Regressors: ICT investment dummy, ICT investment dummy interacted with a district-level indicator of high informality in local labor markets. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 15. Total Employment

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	0.076***	0.073***	0.60***	0.60***
	(0.011)	(0.011)	(0.14)	(0.14)
Δ ICT	0.0072	0.014	0.50***	0.50***
	(0.014)	(0.014)	(0.15)	(0.15)
Δ ICT * High Growth	0.12***	0.10***	0.22***	0.22***
	(0.015)	(0.015)	(0.037)	(0.037)
Observations	3,571	3,571	3,571	3,571

Dependent variable: change in total employment. Regressors: ICT investment dummy, ICT investment dummy interacted with a firm-level indicator variable that is equal to one when the growth in revenue during the sample period is above the median (High Growth). Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE 16. Employment by Worker Type

	Managers		Skilled Workers		Unskilled Workers	
	FE	FE-2SLS	FE	FE-2SLS	FE	FE-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ICT	0.032***	0.20*	0.066***	0.33**	0.043***	0.27**
	(0.011)	(0.10)	(0.012)	(0.15)	(0.010)	(0.12)
Δ ICT	0.010	0.076	0.055***	0.29*	0.022	0.24**
	(0.015)	(0.10)	(0.015)	(0.15)	(0.015)	(0.12)
Δ ICT * Growth	0.041**	0.096***	0.021	0.083***	0.038	0.10**
	(0.017)	(0.028)	(0.019)	(0.031)	(0.024)	(0.047)
Observations	2,432	2,432	2,420	2,420	3,463	3,463

Dependent variable: change in log employment of managers (columns 1 and 2), skilled workers (columns 3 and 4) and unskilled workers (columns 5 and 6). Regressors: ICT investment dummy, and ICT investment dummy interacted with a firm-level indicator variable defined as in Table 15. Instruments defined as in Table 3. Robust standard errors in parenthesis.

TABLE A1. First stage. ICT intensity

	Δ ICT	
	(1)	(2)
Information * Small	0.00064***	0.00062***
	(0.00023)	(0.00023)
Information * Med-size	0.00032**	0.00031**
	(0.00013)	(0.00013)
Information * Large	-0.00028	-0.00030
	(0.00020)	(0.00020)
Observations	3,393	3,381
F-stat	5.22	5.23
Industry effects	Yes	Yes
Trends		Yes

Analogous to Table 3. Dependent variable: average firm investment in ICT over firm sales during the sample period.

TABLE A2. Average wage. ICT intensity

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	-0.49	-0.087	12.5	12.9
	(1.50)	(1.41)	(17.2)	(16.8)
Δ ICT	-0.43	-0.14	11.0	12.7
	(1.47)	(1.40)	(17.0)	(16.8)
Δ Skills	0.31***	0.16**	0.32***	0.15**
	(0.074)	(0.065)	(0.074)	(0.066)
Δ ICT	-3.11	-2.54	-1.57	-0.44
	(1.92)	(1.75)	(15.2)	(15.1)
Δ ICT * High Productivity	6.58**	5.88**	31.6***	32.0***
	(2.59)	(2.45)	(11.7)	(11.7)
Δ Skills	0.31***	0.16**	0.31***	0.15**
	(0.074)	(0.065)	(0.075)	(0.068)
Δ ICT	-2.07	-1.76	1.46	1.70
	(1.59)	(1.48)	(16.3)	(16.2)
Δ ICT * Skills	7.30***	7.19***	28.1***	26.2**
	(2.70)	(2.57)	(10.7)	(10.6)
Δ Skills	0.31***	0.16**	0.31***	0.15**
	(0.074)	(0.065)	(0.074)	(0.067)
Observations	3,259	3,248	3,259	3,248

Analogous to Tables 5 and 6. Regressor: average firm investment in ICT over firm sales during sample period.

TABLE A3. Wage by worker type. ICT intensity

	Managers		Skilled Workers		Unskilled Workers	
	FE	FE-2SLS	FE	FE-2SLS	FE	FE-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ICT	2.32	0.58	-2.55	-8.90	-0.084	25.0
	(1.81)	(24.2)	(1.78)	(17.6)	(1.34)	(16.7)
Δ ICT	-0.0037	0.33	-3.83*	-0.13	-2.95*	-0.29
	(1.65)	(20.1)	(2.21)	(14.5)	(1.78)	(14.8)
Δ ICT * Prod	5.93*	56.2***	3.31	45.9***	7.01***	58.8***
	(3.26)	(18.9)	(3.57)	(13.4)	(2.66)	(11.7)
Δ ICT	0.43	-15.9	-3.30*	-6.24	-1.56	8.40
	(1.76)	(23.0)	(1.76)	(16.0)	(1.44)	(15.9)
Δ ICT * Skills	9.45**	30.5*	3.58	32.5**	6.59*	33.5***
	(3.80)	(16.0)	(4.91)	(12.7)	(3.36)	(11.1)
Observations	2,205	2,205	2,296	2,296	3,146	3,146

Analogous to Table 8. Regressor: average firm investment in ICT over firm sales during sample period.

TABLE A4. Job turnover. Share of unskilled workers. ICT intensity

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	-0.27	-0.83**	-9.00*	-8.23*
	(0.34)	(0.38)	(5.06)	(4.40)
Δ ICT	-0.15	-0.65	-7.18	-5.71
	(0.40)	(0.51)	(5.06)	(4.36)
Δ ICT * High Productivity	-0.28	-0.40	-1.58	-3.59
	(0.60)	(0.59)	(3.36)	(2.89)
Δ ICT	-0.092	-0.59	-9.48*	-8.79**
	(0.32)	(0.39)	(4.93)	(4.30)
Δ ICT * Skills	-0.68	-0.88	-0.84	-0.62
	(0.79)	(0.65)	(4.10)	(3.41)
Δ ICT	1.22	1.22	6.24	14.0
	(1.13)	(1.02)	(5.69)	(9.60)
Δ ICT * Internet	-1.49	-2.06**	-13.6***	-21.6**
	(1.14)	(1.04)	(5.27)	(9.59)
Δ ICT	-0.94*	-0.70	-17.5**	-7.44
	(0.51)	(0.51)	(7.64)	(7.03)
Δ ICT * Computers	0.78	-0.15	11.3**	-0.075
	(0.60)	(0.67)	(5.45)	(5.17)
Observations	3,477	3,475	3,477	3,475

Analogous to Table 13. Regressor: average firm investment in ICT over firm sales during sample period.

TABLE A5. Total Employment. ICT intensity

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ ICT	8.52***	8.67***	15.7	15.7
	(2.55)	(2.45)	(24.3)	(24.3)
Δ ICT	-1.02	-0.14	-88.4**	-88.4**
	(2.09)	(2.04)	(34.9)	(34.9)
Δ ICT * High Growth	20.4***	18.8***	184***	184***
	(4.55)	(4.33)	(22.1)	(22.1)
Observations	3,481	3,481	3,481	3,481

Analogous to Table 15. Regressor: average firm investment in ICT over firm sales during sample period.

TABLE A6. Employment by Worker Type. ICT intensity.

	Managers		Skilled Workers		Unskilled Workers	
	FE	FE-2SLS	FE	FE-2SLS	FE	FE-2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ICT	0.41	14.3	7.86**	25.2	6.11**	-12.2
	(2.07)	(16.9)	(3.27)	(25.5)	(2.69)	(26.0)
Δ ICT	-1.57	-45.5**	4.85	-11.5	2.37	-48.0
	(1.83)	(21.4)	(3.42)	(23.8)	(1.65)	(29.3)
Δ ICT * Growth	4.40	60.6***	6.49	52.4**	8.09	90.6***
	(4.17)	(17.6)	(6.05)	(20.9)	(5.30)	(32.1)
Observations	2,431	2,431	2,419	2,419	3,462	3,462

Analogous to Table 16. Regressor: average firm investment in ICT over firm sales during sample period.