Investment in ICT, Productivity, and Labor Demand*

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Abstract

We explore the causal impact of ICT adoption on firm performance and labor market outcomes using a firm survey from the manufacturing sector in Argentina. We use exogenous exposure to information about technology support programs 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 wages 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, and creation of new occupations. In particular, the adoption of ICT leads to a decrease in the share of unskilled workers and an increase in the number of skilled employees and managers, supporting the view that ICT is complementary with skilled labor. The effect is larger in districts where labor informality is more prevalent.

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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 labor outcomes has a long tradition that spans the literature of skill-biased technical change (Katz and Murphy, 1992), the more recent task-based approach of Autor et al. (2003) and Acemoglu and Autor (2011), and the job polarization arguments of Autor et al. (2006) and Autor and Dorn (2013), among others. The skill-biased technical change literature argues that technology adoption has resulted in a reduction in the demand for unskilled workers. The task-based approach argues that technological change substitutes for workers in performing routine tasks—more amenable to automatization—and complements workers in executing nonroutine tasks—such as problem solving, complex communication, and information-intensive tasks. Using occupational-level data, this strand of literature shows that employment in jobs involving routine tasks has fallen considerably in the US (see also Michaels et al. 2014).[1] The common denominator of these studies is that technology adoption results in negative substitution effects that affect certain types of workers.

In addition to affecting labor demand and employment, innovation and technology adoption are also major factors affecting productivity. 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 in explaining these differences in productivity to otherwise similar firms (see the meta-analysis by Stiroh (2005)). In particular, 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.[2,3]

At the firm level, productivity gains have direct effects on labor demand and wages. Firms that successfully invest in technology enjoy a reduction in costs, an increase in productivity and output growth, which in turn can lead to increases in labor demand through positive output effects. While workers performing routine tasks are prone to being substi-

[1]Regarding job polarization, Autor et al. (2006) present evidence of rising employment in the highest and lowest paid occupations, while Autor and Dorn (2013) find that local labor markets that specialized in routine tasks 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.

[2]See Draca et al. (2006) for a literature review of growth accounting and econometric estimation results.

[3]In Latin America, Crespi et al. (2016) find positive and large effects of innovation on firm labor productivity across 17 countries in 2010 (see also Commander et al. (2011) for an earlier study in Brazil and India). Similarly, in a large sample of Latin American countries in 2010, Grazzi and Jung (2016) show a positive relationship between broadband and firm performance (e.g., probability of innovating and firm productivity).

tuted by technology, workers that are able to work in complement with new technologies may see their demand, productivity, and wages increased.

Increments in wages due to technology adoption may come through several channels. First, there are compositional effects that occur at the firm level. Technology adoption leads to changes in the labor force. The highest paid workers are on average skilled workers who perform non-routinary tasks, that can work in complement with digital technology, and who are not replaced by investment in new technology. Low skilled workers that perform routinary tasks are, instead, more prone to being replaced by technology. A change in labor composition of this nature leads to a decrease in the average wage at the firm level. There are also mechanisms that work at the individual level. One such mechanism is the increase in labor productivity, that results in the increase in wages. Another mechanism works through rent-sharing: increases in profits that occur through innovation spill over to wages in non-competitive labor markets (see Amiti and Davis 2011 and Brambilla 2018).

A large body of empirical studies indeed argues that technology adoption has favored the wage of relatively skilled workers, while simultaneously damaging the wages of the less skilled (see, for example, Autor et al. 1998; Bresnahan et al. 2002; Caroli and van Reenen 2001; O'Mahony et al. 2008). Closely related to digital technologies, Krueger (1993) finds a positive association between the use of computers and wages. More recently Akerman et al. (2015) provide compelling evidence that employment and wages of skilled (unskilled) workers increase (decrease) with broadband internet availability.

Our paper is related to these different strands of literature that link digital technology adoption, productivity, and labor outcomes. Using a panel of Argentine manufacturing firms spanning the period 2010-2012 we study the causal effect of ICT adoption on productivity and wages in an integrated framework and by addressing endogeneity concerns. The novelty of our approach lies in that we provide firm-level evidence on productivity and wage effects of ICT and on the interaction between the two variables as explanations for changes in wages.

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 of researchers and universities.[4] In our empirical analysis we use the exogenous exposure to information

[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 appear generally to be higher than in other developing regions. In 2010, almost 85 percent of firms indicated that they had a high-speed internet

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. The increase in wage occurs even after controlling for skill composition, implying that there are productivity and rent-sharing mechanisms in play. 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. In particular, the adoption of ICT leads to a decrease in the share of unskilled workers and to an increase in the number of skilled workers and managers, supporting the view that ICT is complementary with skilled labor. The effect is larger in districts where labor informality is more prevalent and thus labor adjustment costs are lower.

We further explore complementarities with predetermined firm characteristics. The effects of ICT adoption on productivity are generally found to be largely heterogeneous and a growing literature focuses on firm-level features that explain this heterogeneity, including internal organization, management practices, and labor force composition.[5] In our empirical analysis we find that productivity gains and increases in wages are larger for initially high-productivity and high-skill firms.

Our paper is also related to a recent surge of country case-studies that look into the effects of the adoption of digital technology in Latin America. Some of these studies are Brambilla et al. (2019), for Mexico; Alvarez et al. (2011) and Almeida et al. (2020), for Chile; Viollaz (2019), for Peru; de Elejalde et al. (2015) for Argentina; Monge-González et al. (2011) for Costa Rica; Aboal et al. (2015) for Uruguay; and Crespi et al. (2019) for several countries. See the survey in Dutz et al. (2018).

The paper is organized as follows. In Section 2 we describe the data. Section 3 presents the empirical strategy and Section 4 the results. Section 5 concludes.

2 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 in-

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 ranks in the 56th position among 155 countries in terms of ICT development, right below Chile and Uruguay and above Brazil (ITU, 2012).

[5]See Caroli and van Reenen (2001), Bresnahan et al. (2002), and Brynjolfsson and Hitt (2003), Bloom and Van Reenen (2007), Bloom and Van Reenen (2010) and Bloom et al. (2012).

formation 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 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 thousands of 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 5750 and 1100 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 the 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 and in firms with a manager that has previous experience in a research-related position.

3 Empirical strategy

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

$$\Delta y_{is} = \alpha \Delta ICT_{is} + \gamma x_{is0} + \delta_s + \epsilon_{is} \tag{1}$$

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.

The regression is written in first-differences and, therefore, implicitly includes 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_{i0} 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, medium, and large, 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 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] 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 to invest in ICT for small, medium, and large firms.[8] Our instrument is thus defined as

$$\Delta Z_{is} = INF_{is} \times x_{is0} \tag{2}$$

where INF_{is} is the access to information on the programs and x_{i0} are firm-size groups in the initial period.

[6]See Lopez et al. 2010 for more details about the program FONTAR.

[7]de Elejalde et al. (2015) follow a similar strategy to study the effect of innovation on employment in Argentina for the period 1998-2001.

[8]Crespi et al. (2016) show in a sample of 17 Latin American countries that innovation is strongly correlated with firm size and firm capabilities, and is significantly affected by public support.

4 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.

4.1 Firm performance

In Table 3 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 effect on labor productivity is 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.

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 the specification with and without 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, 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.[9]

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

[9]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, Tables A.1, A.2, A.3, and A.4.

depends on worker and firm characteristics. To study heterogeneous effects across firms, our estimating regression is

$$\Delta y_{is} = \alpha_0 \Delta ICT_{is} + \alpha_1 \Delta ICT_{is} \times \varphi_{is0} + \gamma x_{is0} + \delta_s + \epsilon_{is} \tag{3}$$

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 5.

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 et al. (2018) 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 et al. (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, whereas 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.

4.2 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.[10]

In Table 6 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 panel, 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 6, we further find that the effect of ICT on wages is higher for high-productivity and high-skill firms, as defined in Table 5. This result is consistent with the complementarity findings of Table 5, where ICT results in higher labor productivity, and thus higher marginal product of labor and higher profits, for certain types of firms. Alternatively, workers in high-productivity firms and high-skill workers could have more bargaining power and, thus, are able to participate more in firm profits.

To provide more information on the relationship between investment in ICT and wages,

[10]See Brambilla (2018) for a theoretical model about ICT adoption, employment, and wages.

and to further isolate results from compositional effects, in Table 7 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).[11] 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 7 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 (see Brambilla 2018).

In Tables 8 and 9 we proceed to study the change in labor productivity as a channel linking digital technology adoption and higher wages. The estimating equation is

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

where ΔW_{is} is the change in the average wage, overall and by worker type across different specifications, as in Tables 6 and 7, 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 3 and 5. Estimating equation (4) by 2SLS using the exposure to information as an instrument, is equivalent to a 3-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, results in Table 8 and 9 are more imprecisely estimated than in previous regressions. Coefficients are positive and large but several confidence intervals are large as well. Results are larger and statistically stronger for high-productivity firms in both Table 8 and Table 9. An increase of 10 percent in labor productivity results in an increase of 2.4 percent in wages in high-productivity firms (Table 8); 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 9).

[11] We keep the specifications with firm-specific trends, analogous to columns 2 and 4 in Table 6.

Lastly, in Table 10 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.

4.3 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 11 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.[12] 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 employment turnover: replacing workers, eliminating occupations, and creating new occupations.

In Table 12 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.

[12] 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.

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 13 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.

As a final test, in Table 14 we report estimates for changes in employment due to ICT by worker type. Whereas Tables 12 and 13 document that there is a decrease in the share of unskilled workers, Table 14 further shows that part of the decrease in the share of unskilled workers is due to an increase in the number of skilled workers and managers. Results from Table 14 are inconclusive in terms of whether unskilled employment is reduced, stays the same, or increases.

5 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. In particular, the adoption of ICT leads to a decrease in the share of unskilled workers and an increase in the number of skilled workers and managers, supporting the view that ICT is complementary with skilled labor. The effect is larger in districts where labor adjustment costs are lower (informality is higher). The results from this research exhibit great promise of informing policy debates in Latin American and other middle-income countries where the diffusion and use of ICT has substantially increased in the last decade.

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Tables

Table 1: Descriptive statistics (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			

Notes: This table shows basic descriptive statistics for manufacturing firms with 10 or more employees in the year 2012. Own calculations based on ENDEI (Encuesta Nacional de Dinámica de Empleo e Innovación), 2010-2012.

Table 2: Firm-level predictors of investment in ICT

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	

Notes: This table 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 and manager characteristics in the initial year of data, 2010. Industry controls. Robust standard errors.

Table 3: 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

Notes: This table shows the effect of the adoption of ICT on firm performance. Dependent variables: change in log value added per worker (Panel A) and change in log revenue (Panel B). Regressor: variable indicating whether a firm invested in ICT during the sample period. Instrument: dummy indicating whether a 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 parentheses.

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

Notes: This table reports the first-stage regression of investment in ICT during the sample period on access to information interacted with firm size. Dependent variables: 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. Robust standard errors in parentheses.

Table 5: 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

Notes: This table shows heterogeneous effects of ICT on labor productivity across firms. 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 parentheses.

Table 6: Average wages and investment in ICT

	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

Notes: This table shows the effect of the adoption of ICT on average wages. 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 parentheses.

Table 7: Average wage by worker type and investment in ICT

	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

Notes: This table shows the effect of the adoption of ICT on average wages, broken down by worker type. 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 parentheses.

Table 8: Average wage and investment in ICT: Productivity channel

	FE		FE-2SLS	
	(1)	(2)	(3)	(4)
Δ Productivity	0.041***	0.034***	0.53*	0.50
	(0.0096)	(0.0085)	(0.30)	(0.32)
Δ Productivity	0.037***	0.032***	0.11*	0.10
	(0.011)	(0.0098)	(0.065)	(0.072)
Δ Prod * High Prod	0.016	0.011	0.14**	0.14**
	(0.014)	(0.013)	(0.059)	(0.061)
Δ Productivity	0.035***	0.030***	0.34*	0.31*
	(0.0088)	(0.0085)	(0.18)	(0.18)
Δ 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

Notes: This table explores the change in labor productivity as a channel linking digital technology adoption and higher wages. 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 parentheses.

Table 9: Average wage by worker type and ICT: 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

Notes: This table explores the change in labor productivity as a channel linking digital technology adoption and higher wages. 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 parentheses.

Table 10: Wage gap of skilled-unskilled workers and investment in ICT

	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

Notes: This table analyzes the effect of ICT on the change in the wage gap between skilled and unskilled workers. 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 parentheses.

Table 11: 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

Notes: This table shows descriptive evidence regarding occupational changes for the group of firms that report having gone through some form of innovation during the period of analysis. Each cell corresponds to a separate regression where the dependent variables are three indicators of job turnover: 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 5. All regressions in first differences. Robust standard errors in parentheses.

Table 12: 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

Notes: This table analyzes the change in employment composition by estimating equation (1) with the change in the share of unskilled workers in total firm employment as the dependent variable. 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 parentheses.

Table 13: Job turnover. Share of unskilled workers and informality

	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

Notes: This table analyzes the relation between employment turnover due to ICT and local labor market institutions (informality). 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 parentheses.

Table 14: 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	0.023**	0.16***	0.043***	0.52***	-0.0045**	0.041
	(0.011)	(0.056)	(0.012)	(0.13)	(0.0019)	(0.052)
Δ ICT	0.041***	0.18***	0.035**	0.45***	-0.0074***	0.031
	(0.013)	(0.062)	(0.015)	(0.12)	(0.0022)	(0.045)
Δ ICT * Prod	-0.031**	-0.040	0.013	-0.0051	0.0051*	-0.00027
	(0.015)	(0.027)	(0.016)	(0.033)	(0.0027)	(0.0090)
Δ ICT	0.011	0.15***	0.041***	0.51***	-0.0056***	0.037
	(0.011)	(0.055)	(0.012)	(0.13)	(0.0020)	(0.048)
Δ ICT * Skills	0.044***	0.066***	0.0076	0.068*	0.0042	0.0094
	(0.015)	(0.025)	(0.017)	(0.036)	(0.0031)	(0.0092)
Observations	2,499	2,499	2,469	2,469	3,556	3,556

Notes: 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 firm-level indicator variables defined as in Table 5. Instruments defined as in Table 3. Robust standard errors in parentheses.

A Appendix

Table A.1: 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

Notes: Analogous to Table 4. Dependent variable: average firm investment in ICT over firm sales during the sample period.

Table A.2: 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

Notes: Analogous to Table 6. Regressor: average firm investment in ICT over firm sales during sample period.

Table A.3: 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

Notes: Analogous to Table 7. Regressor: average firm investment in ICT over firm sales during sample period.

Table A.4: 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

Notes: Analogous to Table 12. Regressor: average firm investment in ICT over firm sales during sample period.