ICT adoption and wage inequality: evidence from Mexican firms *

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Abstract

This paper uses a panel of firms from the Mexican Economic Censuses and analyzes at the microeconomic level how labor markets adapt to Information and Communication Technologies (ICT henceforth) adoption by studying its effects over the labor structure of the firm and furthermore, over wages. Thus, it assesses whether increasing ICT use leads to an increasing demand of skilled labor relative to low-skilled and thus, it analyzes its effects on the wage gap between the two groups. The results of this analysis indicate that there is indeed an effect of ICT over the labor demand of higher skilled workers but this does not translate into a higher wage gap between skilled and unskilled workers. These results appear to be driven by an increasing sophistication of blue-collar workers due to the organizational adjustments derived from ICT adoption.

JEL Classifications: E23, F14, L25, O33

Keywords: ICT, jobs, labor demand, skills, technical change, Mexico

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1 Introduction

In recent years, the effect of the ICT adoption over firm-level productivity has been widely studied and there appears to be consensus in terms of the fact that ICT use has indeed important effects over total factor productivity (Syverson, 2011). However, in the framework of theories such as the skill-biased technical change and job polarization, ICT does not only affect this outcome directly but it also entails other effects over the organization and the skill composition of the firm and furthermore, it has broader effects on the whole labor market and income inequality.

Considering that governments increasingly invest in programs aimed at promoting ICT adoption as a mechanism for boosting firm-level productivity, it is important to understand not only the effects of these policies over firm-level performance, but also how they could affect the labor structure and wage inequality.

Most of the studies regarding wages and jobs in the case of Mexico have focused on the effects of its trade opening process, which according to the predictions of theoretical trade models should have decreased the wage gap between unskilled workers and skilled workers considering that Mexico attracted production processes that are intensive in low-skilled labor. However, these effects were not observed during the first decade after the North America Trade Agreement's (NAFTA) entry into force, which has been the most important milestone of this process. These fact led to search for another explanation of the wage dynamics that were observed during this period such as changes in the supply of skilled-labor and the adoption of technologies.

In this paper we analyze the effects of ICT adoption over labor demand of skilled and unskilled workers for the case of Mexico between 2008 and 2013 using data from Mexico's Economic Censuses. Furthermore, we study whether a more intensive use of ICT is associated to a higher wage gap between these two groups. We also take advantage of a very detailed survey regarding ICT use in Mexico (ENTIC 2009 and 2013) in order to analyze some aspects related to planning, organization and the main uses of these technologies that could exhibit changes within the firm due to ICT adoption. In this sense, our main contribution is the analysis of wage-inequality and skilled demand from a firm-level perspective for the case of Mexico, by using microdata (Census and ICT surveys data) that to the best of our knowledge has not been used for this purpose before.

The rest of this paper is organized as follows: Section 2 provides a literature review of studies regarding skill-biased technical change and wage inequality. In section 3, the methodology is presented. Section 4 explains the data used in the analysis as well as some descriptive statistics. Results are discussed in section 5 and conclusions in section 6.

2 Literature Review

During the last decades, the economic literature has focused on explaining the increasing wage inequality in the U.S. that was observed starting in the 1980s and in which the college wage premium raised sharply. Therefore, different empirical studies have explored the role of the demand and supply of skills over the U.S. wage structure. In this framework, the most accepted explanation of these changes is probably the theory of Skill- Biased Technical Change (SBTC). This theory is based on the idea that skilled workers act as a complement of technology, in this case of ICT, while unskilled workers can be substituted by it. Therefore, when new technology is adopted, the demand of skilled relative to unskilled workers increase and accordingly, ceteris paribus the wage gap between these two groups widens, thus increasing wage inequality. These effects in terms of inequality due to these demand shifts can be avoided or compensated by an increasing supply of human capital in what Goldin and Katz (2009) regard as a race between technology and education. In this sense, if the supply of highly-skilled individuals increase at a higher pace than technology and ICT adoption, wage inequality can even exhibit reductions.

Recent studies have departed from the traditional analysis of SBTC and have focused more on the mechanisms through which increases in ICT or technology could be affecting wages and hours worked. In this sense, Autor et al. (2003) and Acemoglu and Autor (2011) focus more on the task content of the different occupations rather than on educational levels. These authors explore how technology and ICT are substitutes for routine tasks but are complements of cognitive-nonroutine tasks which are performed by more skilled and highly educated individuals. Under this framework, middle-skilled individuals could also be working on routine tasks and thus, be vulnerable to being replaced by ICT, which would lead to job polarization. Michaels et al. (2014) analyze how the different occupations and tasks for the U.S are correlated with education and find that indeed more highly educated individuals perform cognitive non-routine tasks, while middle-educated individuals are overrepresented in occupations that require routine tasks but are still more complex than the non-cognitive routine tasks that less-educated workers prefer.

These recent and more sophisticated theories based on tasks, predict positive effects of ICT adoption over demand for more educated individuals, reductions in the demand of medium-skilled individuals but the effects over the less-educated workers are not clear. Authors in the job polarization literature extend the traditional grouping of two skill levels into (low, medium and high) considering that in recent years in countries such as the United Kingdom and Germany, medium-skill occupations have declined relatively to the two tails of the skill distribution (Michaels et al., 2014).

A recent theoretical study by Brambilla (2016) extends this task framework by allowing for firm heterogeneity and differences in wages across firms. This model predicts that as a result of ICT adoption, firms become more specialized in complex tasks and substitute unskilled workers, which is in line with

SBTC models, while the share of skilled workers increase as they are complements of ICT. It also predicts that workers that remain employed (skilled and unskilled) will benefit from an increase in wages. In this sense, skilled workers are expected to exhibit a higher increase in wages considering that the demand for them increase as a result of ICT adoption and that they have more bargaining power. On the other hand, increases for unskilled workers could be the result of a rent-sharing mechanism.

This study is also related to studies that focus on firm organization such as Garicano and Rossi-Hansberg (2006), that analyze the differences in terms of wages between and within managers and production workers. These authors also differentiate between the effects of Information Technologies (IT) adoption and Communications improvements. According to their model, increases in terms of communication technologies allow for production workers to increase their interaction with managers and therefore decisions become more centralized and inequality between them and production workers increases. On the other hand, an increasing use of IT, in terms of better storage and access to knowledge allow for problems to be solved at the different layers of organization increasing the knowledge content of production work and therefore, improving the wages of this kind of workers.

2.1 Empirical studies of wage inequality for Mexico

The literature regarding wage inequality in Mexico has considered two main mechanisms in order to explain the wage dynamics observed during the last three decades. The first one and most studied is trade, considering that Mexico underwent an important process of trade openness during the 1990s, mainly through the entry into force of NAFTA. Therefore, studies have focused on analyzing whether the predictions of the Stolper-Samuelson theorem held for this economy. According to Campos-Vázquez et al. (2014), during the last 30 years there had been two different trends in terms of inequality in Mexico. Between the 1980s and 1996 there was a period of increasing inequality and after that an equalizing period begun. Their analysis suggest that behind both periods were changes in returns, which were driven by increasing demand of skilled labor in the first period and an increasing supply in the second period.

3 Empirical strategy

3.1 Modeling strategy

In order to analyze the effects of ICT use over labor demand of each skill level (proxied as white and blue-collar workers) and over the wage premium of white-collar workers, first of all we start by estimating the effects of increasing ICT use on the absolute demand and wage of workers of each skill level.

$$log(N)_{i,j,t} = \beta_0 + \beta_1 ICT_{i,t} + \gamma x_{i,t} + \alpha_i + u_{i,t} \quad (1)$$

Where:

$log(N)_{i,j,t}$=Logarithm of the Number of workers of skill level j for firm i at time t

$ICT_{i,t}$=ICT use of firm i at time t

$x_{i,t}$=Vector of control variables such as age and capital-per-worker

α_i=firm fixed effects

$$log(W)_{i,j,t} = \beta_0 + \beta_1 ICT_{i,t} + \gamma x_{i,t} + \alpha_i + u_{i,t} \quad (2)$$

Where:

$log(W)_{i,j,t}$=Logarithm of the average wage of workers of skill level j for firm i at time t

j=white-collar, blue-collar

$ICT_{i,t}$=ICT use of firm i at time t

$x_{i,t}$=Vector of control variables such as age and capital-per-worker

α_i=firm fixed effects

Then, we estimate whether the ratio of white-collar workers to blue-collar workers increase as a result of increasing use of ICT and analyze if the wage gap between these two types of workers has increased due to ICT use, which could be an indicator of skill-biased technical change and increasing pressures towards wage inequality.

$$N_W/N_{Bi,t} = \beta_0 + \beta_1 ICT_{i,t} + \gamma x_{i,t} + \alpha_i + u_{i,t} \quad (3)$$

$$W_W/W_{Bi,t} = \beta_0 + \beta_1 ICT_{i,t} + \gamma x_{i,t} + \alpha_i + u_{i,t} \quad (4)$$

Where:

$N_W/N_{Bi,t}$=Number of white-collar/Number of blue-collar workers for firm i at time t

$W_W/W_{Bi,t}$=Wage white-collar/Wage blue-collar for firm i at time t

These equations are estimated throughout this paper using different specifications and different econometric methods in order to test the robustness of our results.

3.2 Instrumental variables

Considering that ICT adoption could be endogenous to the mix and demand of each type of labor, we adopt the same instrumental variable approach used by Iacovone et al. (2016), where the first stage is defined as follows:

$$ICT_{i,j,s,t} = \beta_0 + \phi ICT_{int,j} * ICTHHuse_{s,t} + \beta_1 x_{i,t} + \alpha_i + v_{i,t} \tag{5}$$

Where: $ICT_{i,j,s,t}$= ICT use of firm i from sector j in state s at time t
$ICT_{int,j}$=ICT intensity of sector j in the US
$ICTHHuse_s, t$=Share of households with computers in state s at time t

In order to construct our instrument $ICT_{int,j}{*}ICTHHuse_{s,t}$, we use the ICT-intensity classification included in the Appendix of Bloom et al. (2012) and is based on the revision made by O'Mahony and Van Ark (2003) of the previous ICT-intensity classification from Stiroh (2002). We interact this sectoral variable with the change in household ICT-use at the state level. The use of this second measure is broadly based on Akerman et al. (2015), who take advantage of broadband availability roll-out for Norway as a measure for ICT adoption in order to overcome the endogeneity problem.

To construct this variable we use two alternative sources. The first one is the 2000 and 2010 Population and Housing Censuses, while the second one is the Module on Information Technology Availability and Use in Households (MODUTIH 2010 and 2013).[1] An advantage of our instrument is that the sectoral IT intensity is based on U.S. data, which is by definition exogenous to the decision of Mexican firms and a better measure of "technological characteristics" at the industry level.[2]

[1]Considering that for some states there are great differences between the urban and rural sectors, different versions of these indicators were analyzed restricting the sample to localities with more than 15,000 inhabitants (urban).

[2]We use information from the National Population and Housing Censuses and form the MODUTIH to construct alternative IVS and we use them as separate instruments in the equations. Therefore, we test whether the over-identifying restrictions are valid.

4 Data and Descriptive Statistics

The data used is obtained from the microdata from the Mexico's 2009 and 2014 Economic Censuses, INEGI. Out of the 4,230,745 establishments included in the 2014 Census, we were able to match almost 2,159,804 with the previous census. Considering that the module regarding Science, Technology use and innovation, from which we construct the data regarding ICT use is not applied to microenterprises, which account for 95% of the establishments, our sample is restricted to small, medium and big establishments. We further restricted the sample to firms that had paid workers as the focus of the analysis is on the demand and wages of different types of labor. Additionally, we excluded sectors related to oil and mining as they have different characteristics than the other sectors included in the sample. Therefore, we ended up with a sample of 61,165 firms from the manufacturing, trade and services sectors. The analysis presented focuses on a sample of around 17,000 from the manufacturing sector though some results for the services and trade sectors are presented when we analyze the robustness of these results.

4.1 Firm-level ICT use

Based on the Science, Technology use and Innovation section of the two last Economic Censuses, we use three alternative measures of ICT use. The first two are the share of labor that uses computers and the share of labor that uses the Internet. On the other hand, we take the value of fixed assets related to computer equipment and telecommunications per worker which should be a good measure of the ICT capital stock.[3] As mentioned by Bloom et al. (2015), the two first measures have the advantage of being physical measures which should be recorded consistently across establishments and sectors and that they avoid the use of price deflators. Furthermore, Bloom et al. (2012) use the share of labor with computer in order to test the robustness of their results using an IT stock capital variable, considering that measurement errors in this variable could bias their results.

4.2 Labor and wages

In the case of Mexico, the only way to obtain employee-employer databases is to merge information from the Mexican Social Security Institute (IMSS) with data from any of the National Institute of Statistics and Geography's (INEGI) projects as in Kaplan and Verhoogen (2006). For this study, we were unable to obtain the required authorizations from IMSS to use their information within INEGI's microdata Laboratory. Therefore, in this analysis we use white-collar or non-production workers as a proxy of skilled labor and we associate blue-collar workers to unskilled workers. It is important to note that even though this is a standard

[3] We use producer prices indexes by sector as price deflators for this variable.

approach in the literature mainly due to data limitations, as mentioned by Esquivel and Rodríguez-López (2003) citing Gonzaga et al. (2001) this could be an imperfect association and could lead to results that differ from the ones observed when educational levels are used.

4.3 State household IT-use

In order to construct our instrumental variable, based on Iacovone et al. (2016) we combine ICT sectoral intensity for the US obtained from Bloom et al. (2012) with household ICT use.

Information regarding household IT use at the state level is from the National Population and Housing Censuses 2000 and 2010. We also obtained information from the Module on Information Technology Availability and Use in Households (MODUTIH 2010 and 2013) in order to compare it to the census data.

4.4 Descriptive Statistics

Table 1 shows descriptive statistics for the manufacturing sector. Regarding ICT use as the table shows, the means of ICT use does not appear to have changed much between 2008 and 2013, regardless of the ICT measure that we consider. On average only 26% of workers use computers and only 22% use Internet. However, when we analyze the increase in ICT use by NAICS code in Figure 1 between the two Censuses, we can observe that there is great heterogeneity both in the levels of ICT use and in its growth between 2008 and 2013.

Analyzing our main outcomes of interest, which are wages and labor by skill level, we find that the average number of white-collar workers increased slightly between 2008 and 2013, from around 21 to 23. Something similar was observed with blue-collar workers which increased from an average of 102 to 111 during this period. As both numbers increased, clearly this is due to an overall increase in the average size of the firms considered in the sample. Once again, when we dig further into the composition by NAICS 3-digit code as in Figure 2a, we find that there is heterogeneity as some sectors exhibited great increases in their ratio of white/blue-collar workers while other (mostly labor-intensive sectors) reduced this ratio.

The heterogeneity is even greater in terms of wages, where the chemical, petrochemical sectors as well as machinery and equipment show important wage gaps while in the textile and clothing sectors the gaps are much lower and did not change much between 2008 and 2013 (See Figure 2b).

Analyzing these outcomes at the geographical level, we observe in Figure 3 that the states where there is a higher proportion of white-collar workers relative to blue-collar workers, are the ones that exhibit higher results in terms of economic development and where the most important cities are located: Mexico City, Nuevo León and Jalisco. Accordingly, in the South-East of Mexico, which is the more disadvantaged region of the country, this ratio remains low. It is important to note that between 2008 and 2013 some states in the Central-North region increased this ratio significantly (San Luis Potosí and Querétaro) which is consistent with the emergence of an industrial corridor in what is regarded as the Bajío zone, where the automotive industry has exhibited a high growth rate.

In terms of the wage gap (Figure 4), for 25 states out of the 32, the differences in terms of wages between white and blue-collar workers reduced between 2008 and 2013. The gap increased only in the case of some states of the Central-North region which are part of the Bajío corridor, in Jalisco and in two states which are among the five states with the highest levels of poverty in the country according to Coneval figures for 2013: Oaxaca and Michoacán. The highest wage gaps are observed in the North of the country while the lowest tend to be in the South.

When we analyze ICT use at the firm level proxied by the mean of the share of labor that uses computer (Figure 5), we observe that the firms located in the Central region of the country, mainly Mexico City and its Metropolitan Area tend to use ICT more intensively. Something similar occurs with some states in the North of the country such as Nuevo León. In this case it is clear that the states in the South-East of the country remain lagged even though in all of the states the use of ICT increased.

Figure 6 shows the average of a TFP index calculated at the firm level.[4] In this case we observe once again that in 2008 Mexico City and the State of Mexico were among the states with the highest average levels of firm-level productivity but in 2013 they do not appear in this group anymore while Querétaro and Guanajuato are emerging is highly productive states. On the other hand, Jalisco and Nuevo León were the states with the highest-level of TFP in 2013 according to Census data.

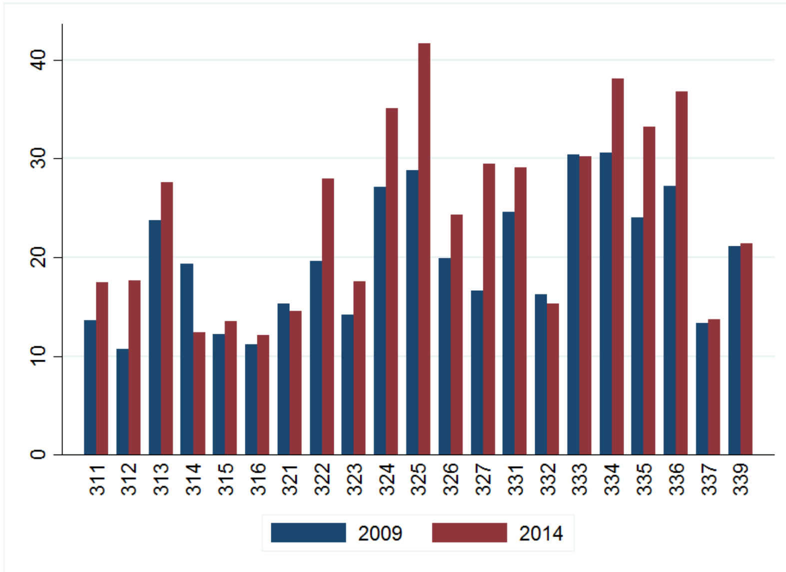
[4]The calculation of this index is based on Aw et al. (2000) as will be explained in more detail in Section 5.

Table 1: Descriptive Statistics: Manufacturing sector

	Mean	sd	p10	p25	p50	p75	p90	N
2008								
ICT variables								
Share of labor that uses computers	26.70	34.75	0.00	0.00	10.00	50.00	90.00	17,548
Share of labor that uses Internet	22.15	30.99	0.00	0.00	8.00	30.00	80.00	17,548
Stock of computer equipment/worker	3.54	4.78	0.33	0.73	1.72	4.18	9.08	17,548
Employment and wages								
Number of white-collar workers	20.89	69.91	1.00	3.00	5.00	14.00	43.00	17,548
Number of blue-collar workers	102.19	287.36	9.00	14.00	28.00	74.00	220.00	17,548
Annual real wage white-collar workers	101.19	88.99	30.00	47.50	74.62	122.21	204.00	17,548
Annual real wage blue-collar workers	51.92	33.06	20.00	30.40	45.18	65.00	90.10	17,548
Firm characteristics								
Capital/worker	189.62	403.00	11.40	31.69	80.13	191.72	418.91	17,548
Total employment	127.53	346.90	13.00	19.00	36.00	95.00	280.00	17,548
Firm age	22.19	14.55	9.00	12.00	18.00	28.00	39.00	17,548
Share of FDI	6.67	24.40	0.00	0.00	0.00	0.00	0.00	17,548
2013								
ICT variables								
Share of labor that uses computers	25.52	30.08	0.00	0.00	15.00	38.00	80.00	17,208
Share of labor that uses Internet	22.87	28.66	0.00	0.00	10.00	30.00	75.00	17,208
stock of computer equipment/worker	3.92	5.14	0.29	0.69	1.83	4.88	10.64	17,208
Employment and wages								
Number of white-collar workers	23.52	79.38	1.00	3.00	6.00	15.00	48.00	17,208
Number of blue-collar workers	110.75	324.37	9.00	14.00	29.00	79.00	230.00	17,208
Annual real wage white-collar workers	100.04	82.46	37.22	51.29	76.10	119.12	192.83	17,208
Annual real wage blue-collar workers	52.54	31.06	23.82	31.76	44.98	65.05	89.34	17,208
Firm characteristics								
Capital/worker	242.94	725.99	11.99	35.87	97.09	238.81	519.38	17,208
Total employment	141.84	400.70	13.00	19.00	38.00	104.00	299.00	17,208
Firm age	20.58	13.83	7.00	11.00	18.00	27.00	38.00	17,208
Share of FDI	8.03	26.65	0.00	0.00	0.00	0.00	0.00	17,208

Source: Authors' calculations with data fromt the 2009 and 2014 Economic Censuses, INEGI

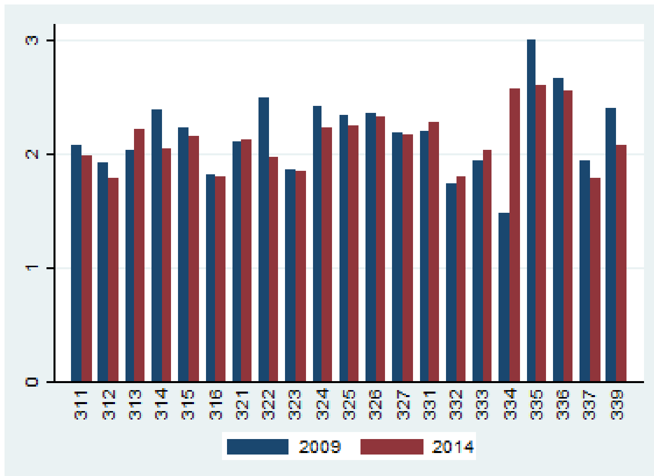
Figure 1: ICT use: share of labor that uses computers by NAICS code: Manufacturing



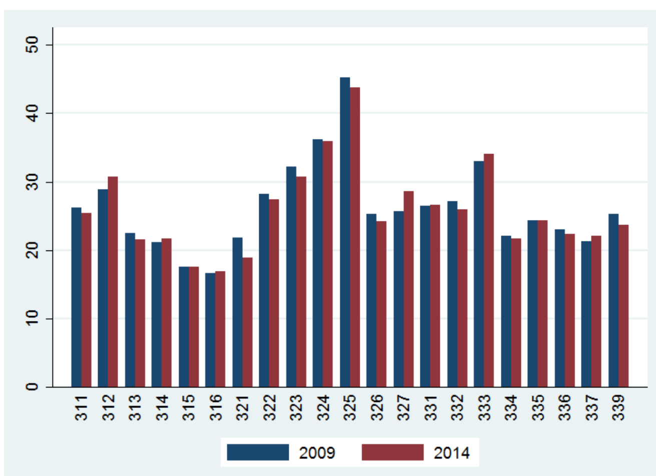
Source: Authors' calculations with data from ENTIC 2009 and 2013, INEGI

Figure 2: Average Labor and Wages gap by NAICS code: Manufacturing

(a) *Number of white/blue-collar workers*



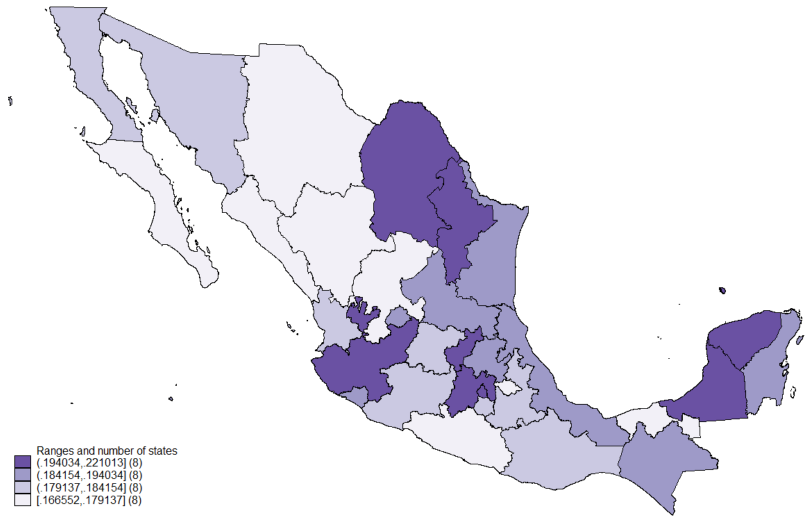
(b) *Wage white/blue-collar workers*



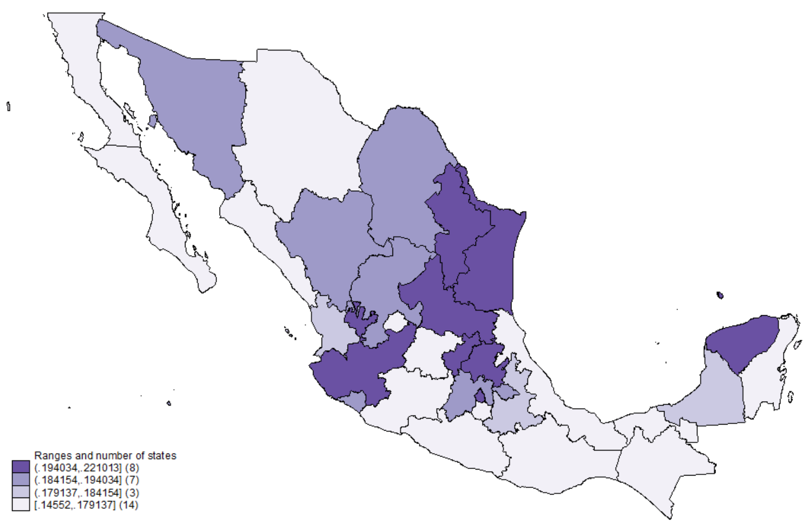
Source: Authors' calculations with data from the 2009 and 2014 Economic Census, INEGI.
Note: The ratios presented are multiplied by 100.

Figure 3: Average Labor ratios by state: Manufacturing

(a) *Number of white/blue-collar workers 2008*



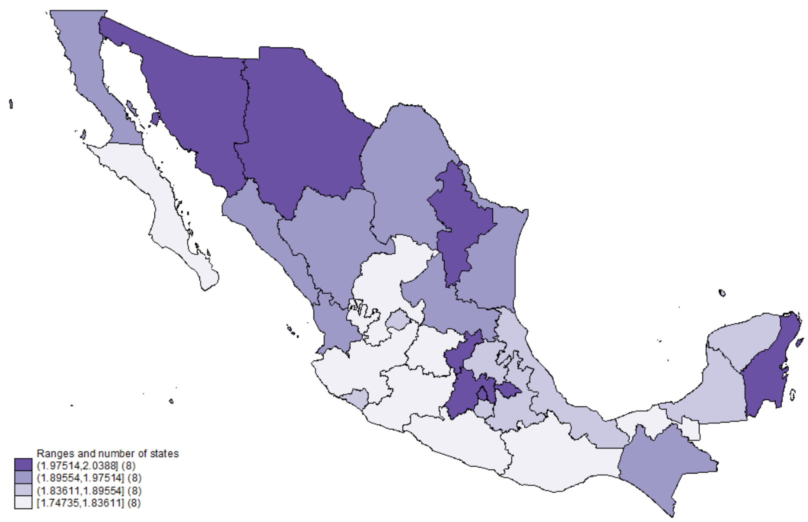
(b) *Number of white/blue-collar workers 2013*



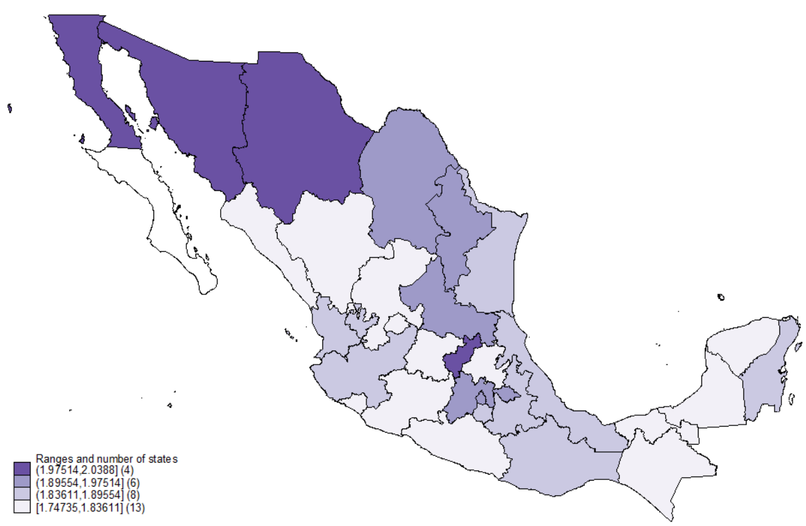
Source: Authors' calculations with data from the 2009 and 2014 Economic Census, INEGI.

Figure 4: Average Wage gap by state: Manufacturing

(a) *Wage gap of white/blue-collar workers 2008*



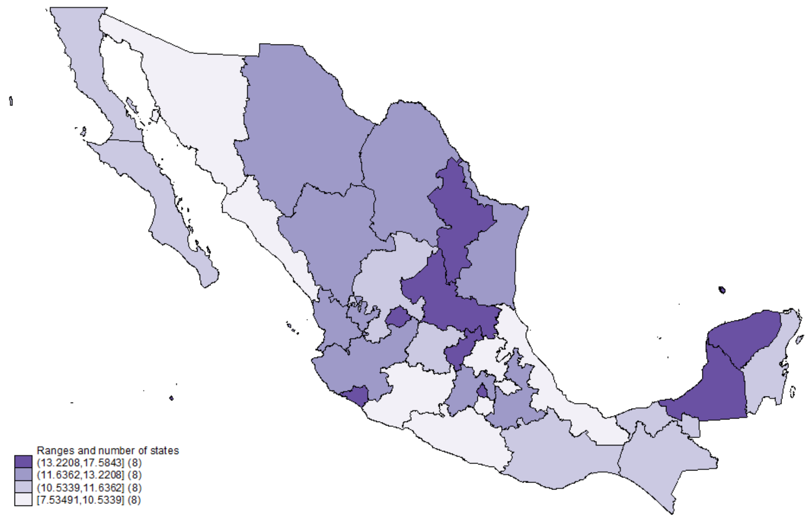
(b) *Wage gap of white/blue-collar workers 2013*



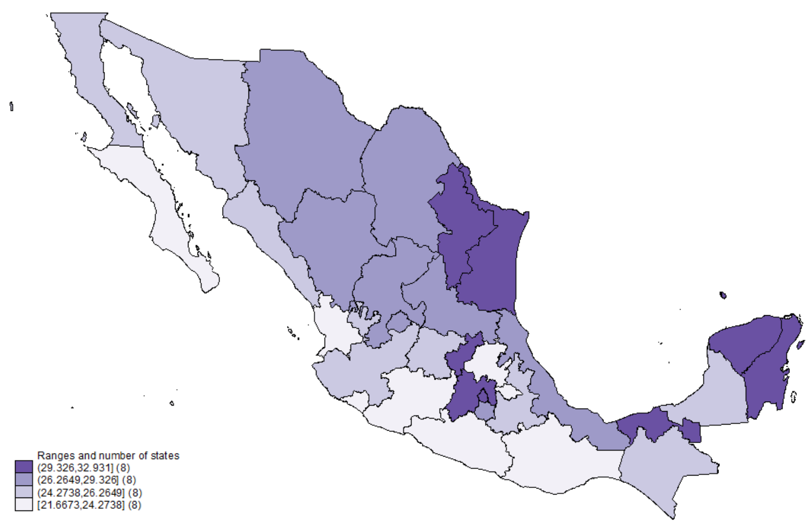
Source: Authors' calculations with data from the 2009 and 2014 Economic Census, INEGI.

Figure 5: ICT use by state: Manufacturing

(a) *Share of labor that uses computers 2008*



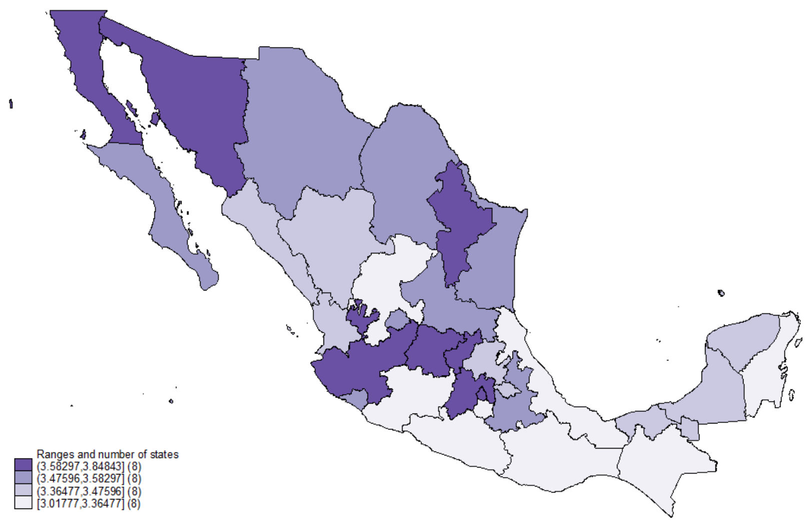
(b) *Share of labor that uses computers 2013*



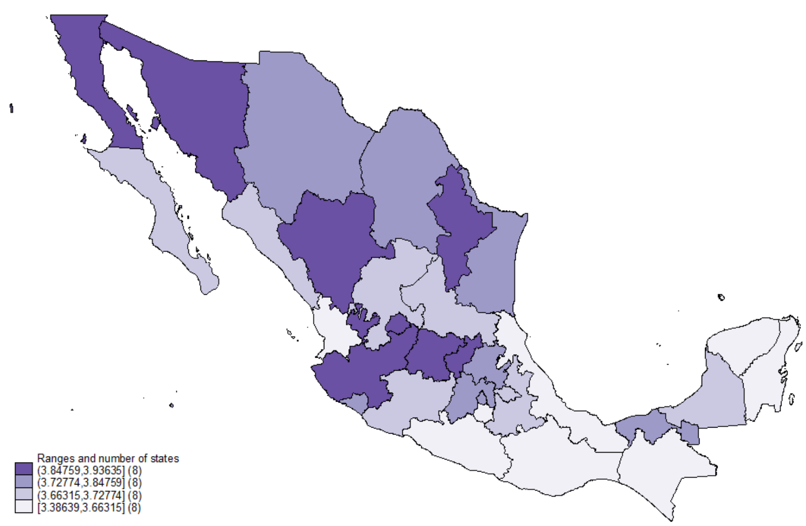
Source: Authors' calculations with data from the 2009 and 2014 Economic Census, INEGI.

Figure 6: TFP by state: Manufacturing

(a) *TFP index 2008*



(b) *TFP index 2013*



Source: Authors' calculations with data from the 2009 and 2014 Economic Census, INEGI.

5 Results

5.1 ICT use, labor demand and wages

Table 2 shows the results of a regression analyzing the relation between ICT use and the number of workers of each skill type in absolute terms. As the table shows, at least when we use physical measures of ICT (share of labor with computer and Internet), positive effects over white-collar employment are observed. The results indicate that a change equivalent to one standard deviation in the share of labor that uses computers is related to a 3.2% increase in the number of white-collar workers. In the case of blue-collar workers, most of the results are not statistically significant when we use physical measures of ICT and in some cases even negative (capital stock of ICT per worker), which is in line with the theory that this type of workers are vulnerable to being substituted by a more intensive use of ICT.

When we analyze the corresponding wages for these two groups in Table 3 we observe that a more intensive use of ICT is positively correlated with wages of both white and blue-collar workers as in most of the specifications the coefficients are positive and statistically significant. In this case a one standard-deviation increase in the share of labor that uses computers is associated to around a 4% increase in white-collar wages and a 2% increase in blue-collar wages.

Estimating an equation of the labor demand ratio of these groups over the use of ICT, we find that regardless of the specification, the coefficients are significant and positive indicating that a more intensive use of ICT is related to a higher ratio of white-collar workers to blue-collar, which is in line with the SBTC theory. Similar results are observed in the case of wages, except for the case of the ICT use proxy related to the capital stock of computer equipment-per-worker, for which results are not robust across specifications.

When we use an instrumental variable approach considering the possible endogeneity of ICT use to the mix of labor that the firms have, we find that the results for the number of workers of each type do not change in direction and significance but now exhibit a higher magnitude, as shown in Table 5. Instrumenting appropriately for ICT, we find that a 10 percentage point increase in ICT use is associated to a 12% increase in the number of white-collar workers while for blue-collar workers results are positive but not statistically significant in most of the specifications and much lower than the coefficients observed for white-collar workers in the cases in which they are significant, indicating that relative to the other group, the number of blue-collar workers decreases as a result of ICT adoption. Accordingly, when we analyze the ratio of white/blue collar workers (Table 7), we observe that it exhibits significant increases in all of the specifications and that the coefficients are higher in magnitude compared to the OLS specification. In this case, a change of 10 percentage points in the share of labor that uses computers is associated to a change of 0.02 in the ratio of

Table 2: OLS regression Number of workers: Manufacturing

	(1)	(2)
Dependent variable: ln(Number of white-collar workers)		
Share of labor that uses computers	0.0009***	0.0009***
	(0.0002)	(0.0002)
Share of labor that uses Internet	0.0012***	0.0011***
	(0.0002)	(0.0002)
ln(stock of computer equipment/worker)	0.0267***	0.0014
	(0.0056)	(0.0056)
Dependent variable: ln(Number of blue-collar workers)		
Share of labor that uses computers	-0.0002	-0.0001
	(0.0002)	(0.0002)
Share of labor that uses Internet	-0.0003	-0.0002
	(0.0002)	(0.0002)
ln(stock of computer equipment/worker)	-0.1209***	-0.0511***
	(0.0057)	(0.0045)
Controls		
ln(capital/worker)	No	Yes
Share of FDI	No	Yes
Age dummies	No	Yes
Size dummies	No	Yes
Fixed effects	Yes	Yes
Observations	34,756	34,756

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

white/blue-collar workers.

Once again, when we use wages of each type as a dependent variable (Table 6), we find that there have been increases in wages for both groups as a result of the increasing adoption of ICT. Furthermore, the magnitudes for blue-collar workers appear to be slightly higher. Therefore, when we estimate the same equation using the wage gap between these two groups as a dependent variable (Table 7), we find that the coefficients are negative and significant indicating a reduction in the wage difference between these two groups. In this case, a 10 percentage point increase in the share of labor that uses computers is associated to a reduction of this ratio in 0.0029, which is really low and consistent with the low change in the average wage gap that is observed in the aggregated data of the Censuses.

Table 3: OLS regression wages: Manufacturing

	(1)	(2)	(3)
Dependent variable: ln(Wage of white-collar workers)			
Share of labor that uses computers	0.0011^{***}	0.0010^{***}	0.0010^{***}
	(0.0002)	(0.0002)	(0.0002)
Share of labor that uses Internet	0.0011^{***}	0.0010^{***}	0.0010^{***}
	(0.0002)	(0.0002)	(0.0002)
ln(stock of computer equipment/worker)	0.0142^{***}	0.0062	0.0035
	(0.0045)	(0.0050)	(0.0050)
Dependent variable: ln(Wage of blue-collar workers)			
Share of labor that uses computers	0.0007^{***}	0.0007^{***}	0.0007^{***}
	(0.0001)	(0.0001)	(0.0001)
Share of labor that uses Internet	0.0008^{***}	0.0008^{***}	0.0008^{***}
	(0.0002)	(0.0002)	(0.0002)
ln(stock of computer equipment/worker)	0.0308^{***}	0.0116^{***}	0.0140^{***}
	(0.0038)	(0.0042)	(0.0042)
Controls			
ln(capital/worker)	No	Yes	Yes
Share of FDI	No	Yes	Yes
Age dummies	No	Yes	Yes
ln(workers)	No	Yes	No
Size dummies	No	No	Yes
Fixed effects	Yes	Yes	Yes
Observations	34,756	34,756	34,756

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: OLS regression share of white-collar/blue-collar workers and wages: Manufacturing

	(1)	(2)	(3)
Dependent variable: white/blue-collar workers			
Share of labor that uses computers	0.0284***	0.0283***	0.0268***
	(0.0060)	(0.0057)	(0.0058)
Share of labor that uses Internet	0.0340***	0.0344***	0.0322***
	(0.0066)	(0.0062)	(0.0063)
ln(stock of computer equipment/worker)	1.9548***	0.8426***	1.1971***
	(0.1594)	(0.1665)	(0.1688)
Dependent variable: white/blue-collar wages			
Share of labor that uses computers	0.0010**	0.0010**	0.0010**
	(0.0004)	(0.0004)	(0.0004)
Share of labor that uses Internet	0.0009*	0.0009*	0.0010**
	(0.0005)	(0.0005)	(0.0005)
ln(stock of computer equipment/worker)	-0.0413***	-0.0150	-0.0261**
	(0.0112)	(0.0123)	(0.0122)
Controls			
ln(capital/worker)	No	Yes	Yes
Share of FDI	No	Yes	Yes
Age dummies	No	Yes	Yes
ln(workers)	No	Yes	No
Size dummies	No	No	Yes
Fixed effects	Yes	Yes	Yes
Observations	34,756	34,756	34,756

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: IV regression Number of workers: Manufacturing

	(1)	(2)
Dependent variable: ln(Number of white-collar workers)		
Share of labor that uses computers	0.0124***	0.0122***
	(0.0029)	(0.0030)
F- first stage	41.42	34.64
Sargan p-value	0.6562	0.7613
Share of labor that uses Internet	0.0099***	0.0097***
	(0.0022)	(0.0023)
F- first stage	78.78 5	66.46
Sargan p-value	0.6145	0.7362
ln(stock of computer equipment/worker)	0.4398***	0.8210**
	(0.1339)	(0.3754)
F- first stage	26.34	6.69
Sargan p-value	0.1945	0.2565
Dependent variable: ln(Number of blue-collar workers)		
Share of labor that uses computers	0.0030	0.0050**
	(0.0021)	(0.0020)
F- first stage	41.42	34.64
Sargan p-value	0.2312	0.4437
Share of labor that uses Internet	0.0024	0.0040**
	(0.0017)	(0.0016)
F- first stage	78.78	66.46
Sargan p-value	0.2220	0.4313
ln(stock of computer equipment/worker)	0.0868	0.3081
	(0.0840)	(0.1943)
F- first stage	26.34	6.69
Sargan p-value	0.1337	0.1835
Controls		
ln(capital/worker)	No	Yes
Share of FDI	No	Yes
Age dummies	No	Yes
Size dummies	No	Yes
Fixed effects	Yes	Yes
Observations	22,590	22,590

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: IV regression wages: Manufacturing

	(1)	(2)	(3)
Dependent variable: ln(Wage of white-collar workers)			
Share of labor that uses computers	0.0141***	0.0129***	0.0134***
	(0.0028)	(0.0030)	(0.0030)
F- first stage	41.42	34.31	34.64
Sargan p-value	0.2636	0.3329	0.3448
Share of labor that uses Internet	0.0113***	0.0103***	0.0107***
	(0.0021)	(0.0022)	(0.0022)
F- first stage	78.78	65.65	66.46
Sargan p-value	0.2354	0.3039	0.3129
ln(stock of computer equipment/worker)	0.5433***	0.7785***	1.0124**
	(0.1373)	(0.2795)	(0.4393)
F- first stage	26.34	11.11	6.69
Sargan p-value	0.9000	0.8948	0.6924
Dependent variable: ln(Wage of blue-collar workers)			
Share of labor that uses computers	0.0184***	0.0190***	0.0182***
	(0.0026)	(0.0029)	(0.0029)
F- first stage	41.42	34.31	34.64
Sargan p-value	0.1256	0.1864	0.1636
Share of labor that uses Internet	0.0148***	0.0152***	0.0145***
	(0.0018)	(0.0020)	(0.0020)
F- first stage	78.78	65.65	66.46
Sargan p-value	0.703	0.1106	0.092
ln(stock of computer equipment/worker)	0.7043***	1.1278***	1.3650**
	(0.1486)	(0.3552)	(0.5441)
F- first stage	26.34	11.11	6.69
Sargan p-value	0.7441	0.7544	0.6001
Controls			
ln(capital/worker)	No	Yes	Yes
Share of FDI	No	Yes	Yes
Age dummies	No	Yes	Yes
ln(workers)	No	Yes	No
Size dummies	No	No	Yes
Fixed effects	Yes	Yes	Yes
Observations	22,590	22,590	22,590

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: IV regression share of white/blue-collar workers and wages: Manufacturing

	(1)	(2)	(3)
Dependent variable: white/blue-collar workers			
Share of labor that uses computers	0.2660***	0.3172***	0.2154**
	(0.0812)	(0.0902)	(0.0858)
F- first stage	41.42	34.31	34.64
Sargan p-value	0.8068	0.9983	0.9022
Share of labor that uses Internet	0.2138***	0.2553***	0.1731**
	(0.0633)	(0.0696)	(0.0677)
F- first stage	78.78	65.65	66.46
Sargan p-value	0.8204	0.9902	0.9072
ln(stock of computer equipment/worker)	8.4320***	14.8560***	12.3146*
	(2.7752)	(5.5414)	(6.3062)
F- first stage	26.34	11.11	6.69
Sargan p-value	0.5797	0.4455	0.5038
Dependent variable: white/blue-collar wages			
Share of labor that uses computers	-0.0276***	-0.0325***	-0.0299***
	(0.0066)	(0.0075)	(0.0073)
F- first stage	41.42	34.31	34.64
Sargan p-value	0.2380	0.2524	0.2249
Share of labor that uses Internet	-0.0221***	-0.0260***	-0.0238***
	(0.0050)	(0.0056)	(0.0055)
F- first stage	78.78	65.65	66.46
Sargan p-value	0.2316	0.2343	0.2097
ln(stock of computer equipment/worker)	-1.0718***	-1.9641***	-2.3037**
	(0.2957)	(0.6885)	(0.9928)
F- first stage	26.34	11.11	6.69
Sargan p-value	0.9843	0.8954	0.7441
Controls			
ln(capital/worker)	No	Yes	Yes
Share of FDI	No	Yes	Yes
Age dummies	No	Yes	Yes
ln(workers)	No	Yes	No
Size dummies	No	No	Yes
Fixed effects	Yes	Yes	Yes
Observations	22,590	22,590	22,590

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2 ICT use and TFP

Considering that the Economic Censuses provide information on capital stock and other expenses, in order to analyze the relation between ICT use and performance, we construct a Total Factor Productivity Measure (TFP). In this case we follow Aw et al. (2000) and we construct a Törnqvist index. Shares are calculated using data from the whole Census.

$$ln(TFP)_i = ln(Y_i) - ln(\overline{Y}) - \Big[\frac{1}{2}\sum_{j=1}^{k}(S_ij + \overline{S_j})(ln(X_{ij}) - ln\overline{X_j})\Big] \tag{6}$$

Where:

$ln(TFP)_i$=TFP index

Y_i=Revenue of firm i

$\overline{Y}$=revenue of average firm

S_{ij}=Revenue share of input j for firm i

$\overline{S_j}$=Average revenue share of input j

j=Payments to labor, capital stock and materials expenses (raw materials, fuel, electricity, etc.)

$\overline{X_j}$=Average value of input j

The results of the effect of ICT use on TFP are shown in Table 8 and indicate that ICT use has indeed an effect over firm-level productivity, even after controlling for other firm characteristics. In this case a 10 percentage point increase in ICT use is associated to a 13% increase in productivity. This result is consistent to what Iacovone et al. (2016) found using a much smaller sample of big firms and a different proxy for performance (sales-per-worker).

Table 8: IV regression TFP: Manufacturing

	(1)	(2)	(3)
Dependent variable: ln(TFP)			
Share of labor that uses computers	0.0142***	0.0126***	0.01364***
	(0.0035)	(0.0038)	(0.0039)
F- first stage	83.24	69.70	69.78
Sargan p-value	0.6220	0.6202	0.6113
Share of labor that uses Internet	0.0118***	0.0103***	0.0112***
	(0.0028)	(0.0031)	(0.0031)
F- first stage	141.3	122.65	122.19
Sargan p-value	0.5550	0.5587	0.5445
Controls			
ln(capital/worker)	No	Yes	Yes
Share of FDI	No	Yes	Yes
Age dummies	No	Yes	Yes
Size dummies	No	No	Yes
Fixed effects	Yes	Yes	Yes
Observations	22,590	22,590	22,590

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Robustness tests

In order to analyze the robustness of our results, we estimated the same OLS regressions but without fixed effects in order to evaluate the sensitivity of our results to unobserved heterogeneity. As Tables 9, 10 and 11 show, the pooled regressions exhibit similar results to the ones of the fixed effects regression and yield the same conclusions as the IV estimates except for the case of the ratio of white/blue-collar wages in which once again, when we do not instrument our ICT use variable, it appears to have positive effects over the wage gap and once we use our instrument these positive effects are not observed anymore.

As previous literature suggests, and consistent with what we analyzed in Iacovone et al. (2016), trade could also be playing a role when we analyze the effects of ICT use. As we are analyzing only the manufacturing sector which tends to be more tradable than the services and trade sectors, we estimated the same regressions for these two sectors in order to analyze whether the effects of ICT over labor demand and wages differ according to sector.

In the case of the number of white-collar workers, it increases in both the trade and services sectors. For services, the coefficients are quite similar to the ones observed in manufacturing but for trade they are much smaller. The results for the number of blue-collar workers are not robust across specification and in the case of the trade sector they are close to zero. In services, when we do not control for other firm characteristics, positive effects are observed. Therefore, very small but significant negative effects are observed in terms of the white/blue-collar workers ratio for both sectors.

In services, wages of both white and blue-collar workers are declining, but the decrease is much higher for white-collar workers, which leads to a reduction in the wage gap. Though the results in terms of the wage gap are qualitatively similar to the ones observed for the manufacturing sectors, the dynamics of these two sectors differ. In the case of the trade sector, wages of white-collar workers increase while for blue-collar workers are decreasing, leading to an increase in the wage gap between these two groups.

Finally, considering the criticism posed by Ciccone and Papaioannou (2010) regarding the use of benchmark industry characteristics interacted with regional characteristics, though it is directed to cross-country models which is not our case[5], we estimated the same models with a different set of instrumental variables in which we used information from Mexico's 1999 Economic Census in order to calculate ICT sectoral intensity. The results (not shown here) do not change much.

[5]This paper indicates that the use of benchmark countries such as the U.S., to account for technology could be biased towards zero or away from zero depending on the technological similarity of the different countries included in the sample vs. the benchmark.

Table 9: Pooled regression Number workers

	(1)	(2)	(3)
Dependent variable: ln(Number of white-collar workers)			
Share of labor that uses computers	0.0112***	0.0045***	0.0049***
	(0.0002)	(0.0001)	(0.0002)
Share of labor that uses Internet	0.0105***	0.0046***	0.0049***
	(0.0002)	(0.0002)	(0.0002)
ln(stock of computer equipment/worker)	0.2109***	0.1474***	0.1356***
	(0.0066)	(0.0042)	(0.0042)
Dependent variable: ln(Number of blue-collar workers)			
Share of labor that uses computers	0.0072***	0.0002*	0.0002**
	(0.0002)	(0.0001)	(0.0001)
Share of labor that uses Internet	0.0064***	0.0001	0.0002
	(0.0002)	(0.0001)	(0.0001)
ln(stock of computer equipment/worker)	-0.0049	-0.0395***	-0.0359***
	(0.0059)	(0.0028)	(0.0028)
Controls			
ln(capital/worker)	No	Yes	Yes
Share of FDI	No	Yes	Yes
Age dummies	No	Yes	Yes
Size dummies	No	Yes	Yes
Sectoral effects	No	No	Yes
Observations	34,756	34,756	34,756

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Pooled regression wages

	(1)	(2)	(3)	(4)	(5)
Dependent variable: ln(Wage of white-collar workers)					
Share of labor that uses computers	0.0030***	0.0006***	0.0013***	0.0008***	0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share of labor that uses Internet	0.0028***	0.0006***	0.0013***	0.0008***	0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ln(stock of computer equipment/worker)	0.0940***	0.0523***	0.0463***	0.0505***	0.0446***
	(0.0031)	(0.0027)	(0.0027)	(0.0028)	(0.0027)
Dependent variable: ln(Wage of blue-collar workers)					
Share of labor that uses computers	0.0013***	-0.0003***	0.0007***	-0.0002**	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share of labor that uses Internet	0.0010***	-0.0004***	0.0006***	-0.0003***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ln(stock of computer equipment/worker)	0.0857***	0.0462***	0.0425***	0.0456***	0.0418***
	(0.0025)	(0.0023)	(0.0023)	(0.0024)	(0.0023)
Controls					
ln(capital/worker)	No	Yes	Yes	Yes	Yes
Share of FDI	No	Yes	Yes	Yes	Yes
Age dummies	No	Yes	Yes	Yes	Yes
ln(workers)	No	Yes	Yes	No	No
Size dummies	No	No	No	Yes	Yes
Sectoral effects	No	No	Yes	No	Yes
Observations	34,756	34,756	34,756	34,756	34,756

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Pooled regression share of white-collar/blue-collar workers and wages

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Number white/blue-collar workers					
Share of labor that uses computers	0.0907***	0.0992***	0.1026***	0.0946***	0.0976***
	(0.0040)	(0.0040)	(0.0043)	(0.0040)	(0.0043)
Share of labor that uses Internet	0.0928***	0.1008***	0.1025***	0.0967***	0.0981***
	(0.0045)	(0.0044)	(0.0047)	(0.0044)	(0.0047)
ln(stock of computer equipment/worker)	4.3636***	3.7940***	3.4614***	3.8239***	3.4925***
	(0.0937)	(0.1034)	(0.1030)	(0.1029)	(0.1025)
Dependent variable: Wages white/blue-collar workers					
Share of labor that uses computers	0.0035***	0.0016***	0.0012***	0.0019***	0.0015***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Share of labor that uses Internet	0.0036***	0.0019***	0.0014***	0.0021***	0.0017***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
ln(stock of computer equipment/worker)	0.0081	0.0052	0.0022	0.0033	0.0005
	(0.0054)	(0.0058)	(0.0058)	(0.0058)	(0.0058)
Controls					
ln(capital/worker)	No	Yes	Yes	Yes	Yes
Share of FDI	No	Yes	Yes	Yes	Yes
Age dummies	No	Yes	Yes	Yes	Yes
ln(workers)	No	Yes	Yes	No	No
Size dummies	No	No	No	Yes	Yes
Sectoral effects	No	No	Yes	No	Yes
Observations	34,756	34,756	34,756	34,756	34,756

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12: IV regression Labor: Services and Trade

	Services		Trade	
	(1)	(2)	(3)	(4)
Dependent variable: ln(Number of white-collar workers)				
Share of labor that uses computers	0.0059^{**}	0.0136^{***}	0.0014^{***}	0.0009^{***}
	(0.0026)	(0.0031)	(0.0004)	(0.0004)
F- first stage	76.13	44.15	718.09	719.07
Sargan p-value	0.8234	0.9701	0.0691	0.0246
Share of labor that uses Internet	0.0151	0.0111^{**}	0.0013^{***}	0.0008^{**}
	(0.0093)	(0.0025)	(0.0003)	(0.0004)
F- first stage	91.73	64.85	2052.99	1012.32
Sargan p-value	0.862	0.8526	0.0746	0.0261
ln(stock of computer equipment/worker)	0.7475^{***}	0.8917^{**}	-0.1986^{**}	0.9119
	(0.1706)	(0.2554)	(0.0698)	(0.6324)
F- first stage	19.55	10.08	23.73	2.730
Sargan p-value	0.1945	0.7481	0.0281	0.7666
Dependent variable: ln(Number of blue-collar workers)				
Share of labor that uses computers	0.0076^{***}	0.0027	0.0003^{**}	0.0000
	(0.0017)	(0.0019)	(0.0002)	(0.0003)
F- first stage	76.13	44.15	718.09	719.07
Sargan p-value	0.5727	0.6191	0.7407	0.8053
Share of labor that uses Internet	0.0069^{***}	0.0022	0.0003^{**}	0.0000
	(0.0017)	(0.0016)	(0.0002)	(.0003)
F- first stage	91.73	64.85	2052.99	1012.32
Sargan p-value	0.2220	0.5726	0.7302	0.8051
ln(stock of computer equipment/worker)	0.3445^{***}	0.2279^{***}	-0.0384	0.0248
	(0.1284)	(0.1390)	(0.0418)	(0.1799)
F- first stage	19.55	10.08	23.73	2.730
Sargan p-value	0.3467	0.7033	0.7698	0.5619
Controls				
ln(capital/worker)	No	Yes	No	Yes
Share of FDI	No	Yes	No	Yes
Age dummies	No	Yes	No	Yes
Size dummies	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	12,276	12,276	16,160	16,160

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 13: IV regression Wages: Services and Trade

	Services		Trade	
	(1)	(2)	(3)	(4)
Dependent variable: ln(Wages of white-collar workers)				
Share of labor that uses computers	-0.0262***	-0.03164***	0.0008**	0.0010**
	(0.0028)	(0.0042)	(0.0004)	(0.0004)
F- first stage	76.13	44.15	718.09	719.07
Sargan p-value	0.7329	0.4922	0.2365	0.5010
Share of labor that uses Internet	-0.0236***	-0.0258***	0.0007**	0.0008**
	(0.0023)	(0.0021)	(0.0003)	(0.0004)
F- first stage	91.73	64.85	2052.99	1012.32
Sargan p-value	0.9541	0.2107	0.2447	0.5159
ln(stock of computer equipment/worker)	-1.0319***	-1.6156***	-0.1755**	0.4739
	(0.2063)	(0.4055)	(0.0685)	(0.4174)
F- first stage	19.55	10.08	23.73	2.73
Sargan p-value	0.3659	0.4919	0.6797	0.1686
Dependent variable: ln(Wages of blue-collar workers)				
Share of labor that uses computers	-0.0085***	-0.0078***	-0.0023**	-0.0014**
	(0.0016)	(0.0020)	(0.0002)	(0.0003)
F- first stage	76.13	44.15	718.09	719.07
Sargan p-value	0.4210	0.6106	0.0089	0.0032
Share of labor that uses Internet	-0.0078***	-0.0066***	-0.0024***	-0.0015***
	(0.0015)	(0.0017)	(0.0003)	(0.0003)
F- first stage	91.73	65.65	2052.99	1012.32
Sargan p-value	0.5339	0.7396	0.0063	0.0025
ln(stock of computer equipment/worker)	-0.3161***	-0.4352***	0.3934***	0.7657**
	(0.1057)	(0.1531)	(0.0568)	(0.3732)
F- first stage	19.55	10.08	23.73	2.73
Sargan p-value	0.6355	0.5938	0.3375	0.0412
Controls				
ln(capital/worker)	No	Yes	No	Yes
Share of FDI	No	Yes	No	Yes
Age dummies	No	Yes	No	Yes
Size dummies	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	12,276	12,276	16,160	16,160

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 14: IV regression white/blue-collar workers and wages: Services and Trade

	Services		Trade	
	(1)	(2)	(3)	(4)
Dependent variable: white/blue-collar workers				
Share of labor that uses computers	-0.0012**	0.0012*	-0.0002**	-0.0007***
	(0.0005)	(0.0006)	(0.0001)	(0.0001)
F- first stage	76.13	44.15	718.09	719.07
Sargan p-value	0.9427	0.96301	0.2961	0.5438
Share of labor that uses Internet	-0.0011***	-0.0007***	-0.0003***	-0.0007***
	(0.0005)	(0.0001)	(0.0001)	(0.0001)
F- first stage	91.73	64.85	2052.99	1012.32
Sargan p-value	0.8563	0.6255	0.3150	0.6255
ln(stock of computer equipment/worker)	0.0820***	0.0882**	-0.0146**	-0.0081
	(0.0310)	(0.0436)	(0.0195)	(0.0895)
F- first stage	19.55	10.08	23.73	2.73
Sargan p-value	0.3596	0.6878	0.7854	0.0001
Dependent variable: white/blue-collar wages				
Share of labor that uses computers	-0.0194***	-0.0252***	0.0080**	0.0071***
	(0.0042)	(0.0058)	(0.0008)	(0.0009)
F- first stage	76.13	44.15	718.09	719.07
Sargan p-value	0.1678	0.3478	0.2829	0.1397
Share of labor that uses Internet	-0.0178***	-0.0211***	0.0073**	0.0064***
	(0.0038)	(0.0047)	(0.0007)	(0.0008)
F- first stage	91.73	64.85	2052.99	1012.32
Sargan p-value	0.2476	0.5465	0.2420	0.1181
ln(stock of computer equipment/worker)	-0.8790***	-1.2897***	0.3081	2.0793
	(0.2002)	(0.3293)	(0.2320)	(1.3825)
F- first stage	19.55	10.08	23.73	2.730
Sargan p-value	0.6922	0.7122	0.8199	0.0033
Controls				
ln(capital/worker)	No	Yes	No	Yes
Share of FDI	No	Yes	No	Yes
Age dummies	No	Yes	No	Yes
Size dummies	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	12,276	12,276	16,160	16,160

Robust standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.4 Mechanisms through which ICT use could affect skill-labor composition within the firm

In order to dig into the mechanisms that could be generating these changes in the skill composition of the labor force within firms, we take advantage of a very detailed survey regarding ICT use in Mexico, the National Survey on ICT, which is designed by the National Council of Science and Technology (CONACYT) and conducted by the National Institute of Statistics and Geography (INEGI). In this case, we use the two last waves of the survey, which almost match with the Census periods as this survey was conducted during 2009 (with information from 2008) and 2013 (with information from 2012). Considering the random design of this survey, we were only able to match slightly more than 600 firms for which we have information in all the relevant variables out of the 6,210 included in ENTIC. It is important to note that due to the construction of this panel, these firms are mostly big firms from the manufacturing sector.

As our measures regarding ICT use are physical measures (share of labor that uses computers and the Internet) which do not provide information on how these technologies are used within the firm and thus linked to productivity, first of all we constructed a set of variables that approximate the use of Enterprise Resource Planning (ERP) systems. Following Garicano and Rossi-Hansberg (2006), as information becomes more widely available across the organization through ERP systems it could be easier for medium-skilled workers, production or even unskilled workers to make more decisions, thus acquiring more sophistication.

We use a question from ENTIC that analyzes the efforts of the firms towards having a better software for human resources, accounting, purchases and payment to suppliers, invoicing, use of information within the firm, sales support, inventories control, which are regarded as administration activities, as well as for production activities (processes control and product design). For each of these activities, we construct a score in which firms that do not use software for these tasks obtain zero and the score increases when firms use more sophisticated or tailor-made software. These scores were normalized so that they range between 0 and 1.

Table 17 shows how the increase in ICT use measured as the share of labor that uses computer is associated with a higher score in terms of administration and production activities. As the results show, a 10 percentage-point increase in ICT use increases the score in around 0.12 for administration activities. Deepening on the activities that are more enhanced within the firm as a result of ICT adoption, in Table 16 we observe that the relation with suppliers, accounting, invoicing and sales are the ones more highly correlated with ICT use. Inventories and Human resources software are also becoming more sophisticated as a result of ICT adoption but at a much smaller rate. On the other hand, there are no effects in terms of payroll and information software. A similar analysis for production activities show that the score in terms of processes and products design are increased equally as a result of a more intensive use of ICT.

In order to also further analyze how Internet is used within the firm, we take advantage of a question regarding whether the firm uses Internet for different purposes and we aggregate them into different scores ranging between 0 and 1 that summarize them. As Table 18 shows, an increasing adoption of ICT measured as the share of labor that uses Internet is more highly correlated with a closer relation with customers and suppliers and human resources (recruiting and training). The only score that is not correlated with ICT adoption is marketing probably because as we are considering big firms, they tend to outsource these services.

Finally, in order to analyze whether ICT adoption is associated to a better communication within the firm, which could affect the organization in terms of the different layers that the firm requires, we analyze how our ICT measures are associated with the number of email accounts that the firm has. As Table 19 show, as expected, as the firm increases its ICT use, the number of email accounts increase significantly regardless of the ICT-use proxy. This could lead to a better communication within the firm which according to the literature could lead to a more centralized decision-making (Garicano and Rossi-Hansberg, 2006).

Table 15: IV regressions of ERP variables on ICT use

	Administration	Production
Share of labor that uses computer	0.0123***	0.0132***
	(0.00355)	(0.00416)
F- first stage	19.08	19.08
Sargan p-value	0.1442	0.1666
N	1,282	1,282

Robust standard errors in parentheses. All estimates include firm fixed effects

* p<0.10, ** p<0.05, *** p<0.01

Table 16: IV regressions of ERP Administration variables on ICT use

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Payroll	HR	Accounting	Suppliers	Invoicing	Information	Sales	Inventories
Share of labor that uses computer	0.00393	0.00833**	0.0189***	0.0201***	0.0239***	0.00311	0.0171***	0.00671*
	(0.00257)	(0.00377)	(0.00617)	(0.00555)	(0.00623)	(0.00462)	(0.00616)	(0.00398)
F- first stage	19.08	19.08	19.08	19.08	19.08	19.08 19.08	19.08	19.08
Sargan p-value	0.7101	0.7205	0.1506	0.1050	0.1965	0.6970	0.3127	0.0388
N	1,282	1,282	1,282	1,282	1,282	1,282	1,282	1,282

Robust standard errors in parentheses. All estimates include firm fixed effects. * p<0.10, ** p<0.05, *** p<0.01

Table 17: IV regressions of ERP Production variables on ICT use

	Processes	Products
Share of labor that uses computer	0.0139***	0.0125***
	(0.00488)	(0.00464)
F- first stage	19.08	19.08
Sargan p-value	0.1283	0.3670
N	1,282	1,282

Robust standard errors in parentheses. All estimates include firm fixed effects

* p<0.10, ** p<0.05, *** p<0.01

Table 18: IV regressions of Internet use scores on ICT use

	Internet use	Information	Customers and Suppliers	Payments and finance	Marketing	Human Resources
Share of labor that uses internet	0.0145***	0.00540***	0.0288***	0.00656***	-0.000612	0.0272***
	(0.00215)	(0.00183)	(0.00459)	(0.00230)	(0.00410)	(0.00416)
F- first stage	34.81	34.81	34.81	34.81	34.81	34.81
Sargan p-value	0.3632	0.6490	0.2352	0.7200	0.4281	0.8055
Observations	1,282	1,282	1,282	1,282	1,282	1,282

Standard errors in parentheses. All estimates include firm fixed effects

* p<0.10, ** p<0.05, *** p<0.01

Table 19: IV regressions of Number of email accounts on ICT use

Dependent variable: Number of email accounts	
Share of labor that uses computer	13.06***
	(4.244)
F- first stage	19.08
Sargan p-value	0.7505
Share of labor that uses Internet	11.57***
	(3.996)
F- first stage	19.08
Sargan p-value	0.2908
N	1,282

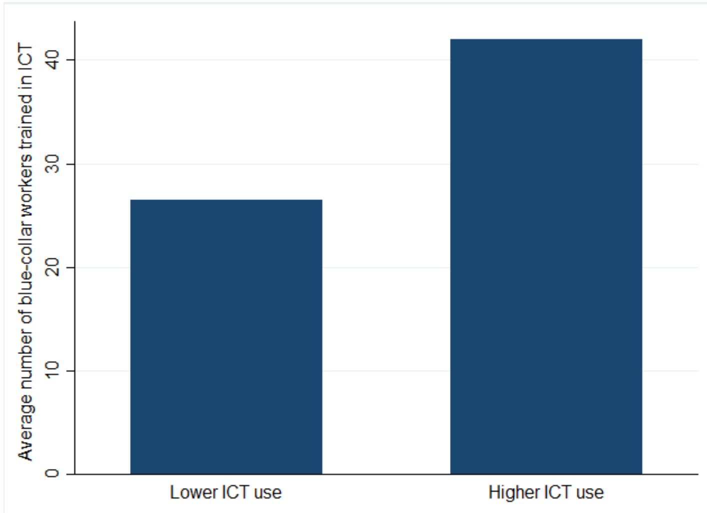
Standard errors in parentheses. All estimates include firm fixed effects

* p<0.10, ** p<0.05, *** p<0.01

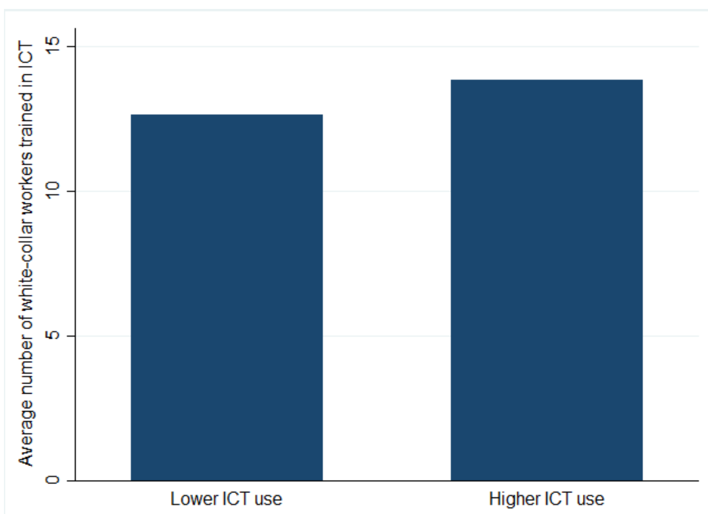
Considering that one of the possible explanations for the increase in wages of blue-collar workers is that they are becoming more sophisticated and thus, some of them instead of being substituted by ICT are becoming complements of these technologies, we analyze a variable regarding the number of workers that are trained in ICT according to their skill-level (white-collar and blue-collar). As Figure 7 shows, firms that make more intensive use of ICT provide more training for both white and blue-collar workers, but the difference is much higher and significant when blue-collar workers are considered. This is an expected outcome, considering that white-collar workers are not supposed to require much training as they are assumed to be initially more skilled. However, in the case of blue-collar workers as the average number of workers trained is much higher in firms that use ICT more intensively, it is an indicator that they are using these technologies and thus, upgrading their skills.

Figure 7: Training in ICT: Manufacturing

(a) *Average number of blue-collar workers trained in ICT*



(b) *Average number of white-collar workers trained in ICT*



Source: Authors' calculations with data from ENTIC 2009 and ENTIC 2013, INEGI.

6 Conclusions

ICT use and technology adoption are factors that are not only associated to positive effects over productivity, but also that have important effects over the firm organization and labor demand and therefore, over wages of different levels of skills as explained through the literature regarding skill-biased technical change and job polarization. Therefore, the analysis of this process at the firm level is important for explaining the dynamics of wage inequality at the country levels.

In this paper we analyzed the relation between ICT adoption and labor demand of white and blue-collar workers and the corresponding changes in terms of the wage gap between these two groups for the case of Mexico between 2008 and 2013 using a firm-level panel of manufacturing firms from the two last Economic Censuses. Our results indicate that ICT adoption has indeed increased the labor demand of more highly skilled workers, approximated by white-collar workers relative to blue-collar workers, which is indicative of firms upgrading their skill mix due to ICT adoption. However, similar effects are not observed in terms of the wage gap between these two groups as both of them exhibit wage increases and furthermore, as the effects of ICT on the wage gap are negative.

A possible explanation for these results, which is supported by the analysis of ICT related variables obtained from a detailed survey regarding ICT for Mexico is that blue-collar workers are becoming more sophisticated as a result of an increasing availability of information within the firm due to the increasing use of ERP systems as well as an increasing training of blue-collar workers in these technologies.

Other alternative explanations could be associated to rent-sharing mechanisms as explained in Brambilla (2016) or to the job polarization literature in which as explained in Michaels et al. (2014) for medium-skilled workers the effects of ICT on wages are negative against low-skilled workers. In this sense, the presence of medium-skilled workers in both of the white-collar and blue-collar workers could lead us to underestimate the real effect on the wage gap between high-skilled and low-skilled workers. However, to appropriately test this last hypothesis we would need more detailed information regarding tasks and education of workers which could only be obtained through an employee-employer matched database, which is not available in the case of Mexico.

It is also important to note that heterogeneity is observed in terms of sectors as even though the services sector also shows a decrease in the wage gap between white and blue-collar workers, this result has a different explanation as wages for both groups decreased as a result of ICT adoption. On the other hand, for the trade sector, an increasing ICT use is associated with a higher wage gap between these two groups.

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