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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 the adoption of information and communication technologies. The paper studies the effects of the adoption of information and communication technologies over the labor structure of the firm and wages. Thus, it assesses whether increasing the use of information and communication technologies leads to an increasing demand for skilled relative to low-skilled labor, and, thus, analyzes its effects on the wage gap between the two groups. The results of this analysis show that there is indeed an effect of the adoption of information and communication technologies over the demand for higher-skilled workers. However, for the manufacturing and services sectors, instead of increasing the wage gap between skilled and unskilled workers, the wage gap decreases. The results for the manufacturing sector appear to be driven by an increasing sophistication of blue-collar workers due to the organizational adjustments derived from the adoption of information and communication technologies.

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ICT Adoption and Wage Inequality: Evidence from Mexican Firms*

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1 Introduction

In recent years, the effect of ICT adoption over firm-level productivity has been widely studied and there appears to be consensus about the importance of ICT for firms' performance (Syverson, 2011). However, in the context of models of Skill-Biased Technical Change (SBTC), ICT also affects firms' organization, skill composition, demand for labor and therefore, wage inequality.

Since 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 labor demand and wage inequality.

Most of the studies analyzing labor market outcomes, either in the framework of the SBTC theories or in the more recent skills and tasks (Autor et al., 2003; Acemoglu and Autor, 2011) and polarization (Michaels et al., 2014) strands of the literature, have focused on these outcomes for the case of developed countries, which tend to have better data availability for these kinds of analyses. Therefore, the evidence on ICT use and labor for developing countries is still scant.

Moreover, the small set of papers that have studied the impact of exogenous shocks on wages and labor demand 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 American Free Trade Agreement's (NAFTA) entry into force, which has been the most important milestone of this process. This 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.

This paper analyzes 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 better understand some of the mechanisms that can explain what firms do when adopting ICT. Our main contribution is the analysis of wage-inequality and demand for skilled labor from a firm-level perspective for the case of Mexico, by using novel firm-level microdata (Census and ICT survey data) that to the best of our knowledge has not been used for this purpose before. A second contribution is the study of this relation for three different sectors (manufacturing, services and commerce), given the fact that the literature has focused on manufacturing due to its importance for productivity growth.

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 led to a sharp increase in the college wage premium. Accordingly, 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 for skilled relative to unskilled workers increases and, 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 framework, if the supply of highly-skilled individuals increases 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. 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 perform.

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 for 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 three (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 increases 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 since the demand for them increases as a result of ICT adoption and they have more bargaining power. On the other hand, increases for unskilled workers could be the result of a rent-sharing mechanism.

This paper 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 the use 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. In contrast, an increasing use of IT, in terms of better storage and access to knowledge, allows 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 to explain the wage dynamics observed during the last three decades. The first one and most studied is trade, given the fact 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 began. Their analysis suggests that behind both periods were changes in returns, which were driven by increasing demand for skilled labor in the first period, and an increasing supply in the second period.

3 Empirical Strategy

3.1 Modeling strategy

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, we start by estimating the effects of increasing ICT use on the absolute demand and wage of workers of each skill level. As our econometric estimates rely on a database that only has two periods, we estimate our equations in differences, which is equivalent to the inclusion of fixed effects:

$$\Delta log(N)_{i,j} = \beta_1 \Delta ICT_i + \gamma_1 x_{1,i,t_0} + \gamma_2 \Delta x_{2,i} + u_i \tag{1}$$

Where:

$\Delta log(N)_{i,j}$= Difference of logarithms of the number of workers of skill level j for firm i between t_0 and t_1

j=white-collar, blue-collar

ΔICT_i=Change in ICT use of firm i between t_0 and t_1

x_{1,i,t_0}=Vector of control variables such as age and size group at time t_0

$\Delta x_{2,i}$=Vector of the change of control variables such as capital per worker between t_0 and t_1

$$\Delta log(W)_{i,j} = \beta_1 \Delta ICT_i + \gamma_1 x_{1,i,t_0} + \gamma_2 \Delta x_{2,i} + u_i \tag{2}$$

Where:

$\Delta log(W)_{i,j,t}$=Difference of logarithms of the average wage of workers of skill level j for firm i between t_0 and t_1

j=white-collar, blue-collar

ΔICT_i=Change in ICT use of firm i between t_0 and t_1

x_{1,i,t_0}=Vector of control variables such as age and size group at time t_0

$\Delta x_{2,i}$=Vector of the change of control variables such as capital per worker between t_0 and t_1

Then, we estimate whether the ratio of white-collar workers to blue-collar workers increases as a result of ICT adoption 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.

$$\Delta N_W/N_{B_i} = \beta_1 \Delta ICT_i + \gamma_1 x_{1,i,t_0} + \gamma_2 \Delta x_{2,i} + u_i \tag{3}$$

$$\Delta W_W/W_{B_i} = \beta_1 \Delta ICT_i + \gamma_1 x_{1,i,t_0} + \gamma_2 \Delta x_{2,i} + u_i \tag{4}$$

Where:

$\Delta N_W/N_{B_i}$=Difference in the number of white-collar/number of blue-collar workers for firm i between t_0 and t_1

$\Delta W_W/W_{B_i}$=Difference in the wage of white-collar/wage of blue-collar workers for firm i between t_0 and t_1

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

3.2 Instrumental variables

ICT adoption could be endogenous to the mix and demand for each type of labor. Therefore, we adopt an instrumental variable approach following Iacovone et al. (2016), where the first stage is defined as follows:

$$\Delta ICT_{i,j,s} = \beta_0 + \phi_1 ICT_{int,j} * Average\,elevation_s + \phi_2 ICT_{int,j} * CV(locality\,elevation)_s + \beta_1 x_i + v_i \tag{5}$$

Where:

$\Delta ICT_{i,j,s,t}$= Change in ICT use of firm i from sector j in municipality s between t_0 and t_1

$ICT_{int,j}$=ICT intensity of sector j in the US

$Average\,elevation_s, t$=Average elevation of municipality s

$CV(locality\,elevation)_s$=Coefficient of variation localities elevation for municipality s

Similarly to Iacovone et al. (2016), we construct our instruments using the ICT-intensity classification from the Appendix of Bloom et al. (2012), which 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 average elevation of the municipality and with the coefficient of variation of locality elevations. The rationale behind the use of average elevation and its coefficient of variation at the municipality level, is based on the difficulties associated with the implementation of Internet technologies at the geographical level. According to the Federal Institute of Telecommunications (IFETEL), in Mexico the main technology used to provide broadband is DSL cable, followed by Modem cable, optical fiber and microwave connections with still a very small share of satellite connections. Among these technologies, the only one that appears not to be restricted by terrain elevations is satellite, as in the case of cable-based technologies, in order to cover mountain regions, a greater length of cable is required, which represents higher costs. Furthermore, in the case of microwave technologies, an important requirement is that the towers need to have point-to-point visual, which is really difficult in the case of these types of regions. Therefore, we consider the average level of elevation of each municipality obtained from raster pictures of the country (INEGI). It is important to note that, even though in the last two decades highway construction has established infrastructure to increase the supply of optical fiber, the use of this technology is still very low in Mexico, which makes the highway networks a not very good instrument. The use of this instrument is broadly based on Akerman et al. (2015), who take advantage of broadband availability roll-out for Norway as a measure for ICT adoption with the purpose of overcoming the endogeneity problem, and on Duflo and Pande (2007) and Manacorda and Tesei (2016), who use geographical factors (rivers' gradients and incidence of lightning) as instruments for dam construction and mobile technology infrastructure, respectively.

As Figure 1 shows, the continuum of elevations taken from raster pictures of the country, was translated into polygons (municipalities and localities) to calculate the two indicators for the construction of these instruments.

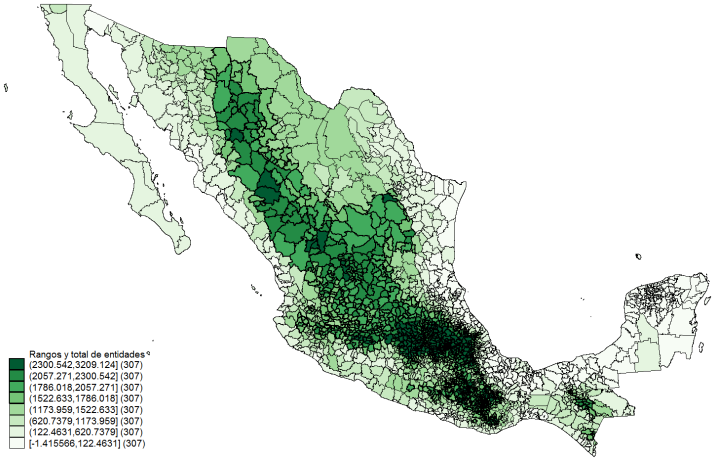
An advantage of our instrument is that the sectoral ICT intensity is based on U.S. data, which are by definition exogenous to the decision of Mexican firms and a better measure of "technological characteristics" at the industry level.[1] Furthermore, as we are using a geographical indicator to account for ICT availability, it is clear that the instrument should be exogenous.

[1] We use different definitions of sectoral IT intensity based on this literature, which distinguishes IT producing and IT using industries. Therefore, we test whether the over-identifying restrictions are valid.

Figure 1: Mexico's elevations

(a) *Raster picture of Mexico's elevations*

(b) *Elevations translated into polygons (municipalities)*



Source: Iacovone et al. (2016) with Geographical data from INEGI.
Note: The authors used ArcMap to translate elevations into averages for municipalities.

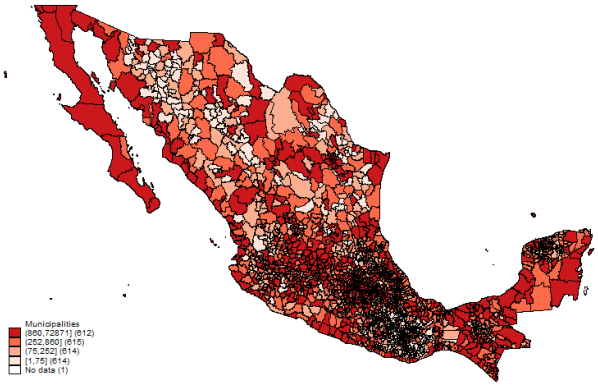
4 Data and Descriptive Statistics

The data used were obtained from microdata of 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, that is, around 50% of the total universe in 2013. The main reason behind this match rate is the dynamics of firm demography. 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. Therefore, our sample is restricted to small, medium and big establishments.[2] 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. We ended up with a sample of 26,000 firms from the manufacturing, commerce and services sectors.[3]

We tested whether the match rate between the two Censuses is correlated with the components of our instrumental variable (sectoral ICT intensity and municipality elevations). We found that the correlation between municipality elevations and the number of unmatched firms at the municipality level is 0.02, while the correlation between sectoral ICT use and the number of unmatched establishments by sector is 0.03. Furthermore, as shown in Figure 2 the number of unmatched establishments appears to be evenly distributed across the country.

Figure 2: Geographical distribution of unmatched establishments



Source: Authors' calculations using data from the 2014 Economic Census, INEGI.

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.[4] 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

[2]Some small firms do not include the module on Science, Technology use and innovation either.

[3]See Appendix A for further information on the construction of the sample.

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

deflators. Furthermore, Bloom et al. (2012) use the share of labor with computer to test the robustness of their results using an IT stock capital variable, as 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 for skilled labor and we associate blue-collar workers to unskilled workers.[5] As Tables 1, 2, and 3 show, the means for wages are consistent with this approximation. It is important to note that, even though this is a standard 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. Throughout the paper we use interchangeably the terms skilled (unskilled) and white-collar (blue-collar) workers.

4.3 Descriptive Statistics

Tables 1, 2, and 3 show descriptive statistics for the manufacturing, services and commerce sectors. The manufacturing sector is the one that started with a higher level of average ICT use in 2008, slightly higher than the one observed for services and much higher than the one for commerce. However, the means of ICT use in the manufacturing sector do not appear to have changed much between 2008 and 2013, regardless of the ICT measure that we consider, while for the other two sectors we observe sharp increases in ICT use. For 2014, on average only 28% of workers in the manufacturing sector use computers and only 26% use Internet, while the equivalent figures for services are 34% and 33%, respectively. Moreover, for establishments in the commerce sector, 45% of workers use computers and 42% use Internet.

When we analyze the increase in ICT use by NAICS code in Figure 3 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, regardless of the sector. For example, in the manufacturing industry, subsectors such as computer

[5]The Economic Census classifies workers into white-collar and blue-collar workers. In this case, the first category includes all workers related to administrative areas, accounting and management activities. Blue-collar workers are all employees that participate in activities related to production, sales and direct services; that is, to operations depending on the sector.

equipment and electronic apparatus, the printing industry, the production of transportation equipment as well as the petrochemical and chemical sectors, exhibit great increases in their use of ICT, while more traditional sectors such as apparel, leather and furniture, show low levels of ICT use which do not vary much across time. In the case of the services sector, mainly transportation and other services related to this subsector, along with information, software and publications and the electronic processing of accommodation and related services, exhibit the highest levels of ICT adoption during the period of analysis. Finally, for commerce, great increases in ICT use are observed for subsectors such as apparels and footwear retail, as well as commerce of health products. The changes for this last sector could in part be related to the increasing adoption of e-commerce.

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 24 to 27 employees for the manufacturing sector. Similar figures are observed for the services sector, while the commerce sector exhibits a much lower number of white-collar workers (around 9 employees). This is consistent with the fact that firms in this sector tend to be small, relative to the other two sectors.

Something similar was observed for blue-collar workers in the manufacturing industry, which increased from an average of 123 to 127 workers during this period. Once again, comparable magnitudes are observed for the services sector, while for commerce, the number of blue-collar workers is on average of 24 and this figure does not change much between 2008 and 2013.

As the numbers of white and blue-collar workers increased in the manufacturing sector, clearly there is 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 4, we find that there is great heterogeneity as some subsectors exhibit much higher white/blue-collar ratios. For example, for the manufacturing industry, the chemical and petrochemical sectors, along with machinery and equipment have the highest ratios while other sectors such as clothing, leather and wood products have a low proportion of white-collar workers. However, these ratios do not appear to change much over time.

Similar heterogeneity is observed in terms of wages. Though on average the wages of white-collar workers are two times the ones of blue-collar workers regardless of the sector, the magnitude of these gaps varies across NAICS 3-digits codes. As Figure 5 shows, the biggest gaps for manufacturing are observed in electrical apparatus, computer equipment and transportation equipment. On the other hand, sectors such as leather, printing and furniture exhibit the lowest wage gaps. Additionally, between 2008 and 2013, these ratios changed significantly for some sectors. As depicted in the figure, the wage ratio increased for computers and equipment, finished textiles and machinery and equipment.

In the case of the services sector, the highest wage ratios are observed for restaurants and electronic

processing of accommodation services. This last sector exhibited an important decrease in the wage gap between 2008 and 2013. Similarly, water transportation showed a decrease in this ratio. On the other hand, for the commerce sector, increases in the wage gap are observed in most of the subsectors.

Through the analysis of these outcomes at the geographical level, for the manufacturing sector we observe in Figure 6 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. Similar figures for the Services and Commerce sectors are shown in Appendix B. For these other two sectors, the geographical patterns are not as clear as in the Manufacturing sector. For the Services sector, the highest white/blue-collar ratios are observed in the South and North East of the country while for commerce in the Northern region.

In terms of the wage gap (Figure 7), for 25 states out of the 32, the differences in terms of wages between white and blue-collar workers in the manufacturing sector 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. For the services and commerce sectors, the graphs shown in Appendix B indicate that, once again, different states exhibit the highest white/blue-collar wage ratios in comparison to manufacturing. For services, the states with the highest wage gaps in 2013 are distributed across the country, while for commerce most of them are neighboring states in the Pacific Coast (Nayarit, Jalisco, Colima, Michoacán and Guerrero).

When we analyze ICT use at the firm level proxied by the mean of the share of labor that uses computer (Figure 8), we observe that 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. The services and commerce sectors show similar results for this variable (Appendix B).

Figure 9 shows the average of a TFP index calculated at the firm level for the manufacturing

industry.[6] 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 as 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.

[6]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	30.82	35.31	0.00	0.00	15.00	50.00	100.00	11,438
Share of labor that uses Internet	25.56	31.68	0.00	0.00	10.00	40.00	85.00	11,438
Stock of computer equipment/worker	3.54	4.48	0.34	0.78	1.83	4.41	8.95	11,438
Employment and wages								
Number of white-collar workers	24.33	79.23	2.00	4.00	7.00	17.00	51.00	11,438
Number of blue-collar workers	122.92	318.47	11.00	17.00	37.00	96.00	276.00	11,438
Annual real wage white-collar workers	107.67	90.35	32.40	50.00	80.50	132.21	218.47	11,438
Annual real wage blue-collar workers	52.88	32.44	21.00	31.20	46.24	66.41	91.57	11,438
White/Blue-collar workers	0.25	0.22	0.06	0.10	0.19	0.33	0.54	11,438
White/Blue-collar wages	2.19	1.42	0.92	1.21	1.76	2.76	4.15	11,438
Firm characteristics								
Capital/worker	194.46	392.10	11.48	33.45	84.44	201.33	433.92	11,438
Total employment	151.66	387.31	15.00	24.00	48.00	121.00	334.00	11,438
Firm age	23.01	14.83	9.00	13.00	19.00	29.00	41.00	11,438
Share of FDI	8.21	26.88	0.00	0.00	0.00	0.00	0.00	11,438
2013								
ICT variables								
Share of labor that uses computers	28.27	30.39	0.00	5.00	20.00	40.00	85.00	11,438
Share of labor that uses Internet	25.57	29.10	0.00	3.00	15.00	35.00	80.00	11,438
Stock of computer equipment/worker	4.28	5.32	0.32	0.80	2.16	5.60	11.36	11,438
Employment and wages								
Number of white-collar workers	27.08	87.54	2.00	3.00	7.00	19.00	56.00	11,438
Number of blue-collar workers	126.64	352.21	10.00	17.00	36.00	98.00	265.00	11,438
Annual real wage white-collar workers	105.31	85.46	39.04	53.60	79.41	126.27	202.53	11,438
Annual real wage blue-collar workers	54.07	31.95	24.82	32.67	46.07	67.48	91.91	11,438
White/Blue-collar workers	0.26	0.23	0.06	0.10	0.19	0.33	0.57	11,438
White/Blue-collar wages	2.09	1.24	0.96	1.28	1.74	2.53	3.68	11,438
Firm characteristics								
Capital/worker	249.08	696.11	11.98	38.01	102.67	254.98	544.35	11,438
Total employment	160.31	424.70	15.00	23.00	48.00	127.00	342.00	11,438
Firm age	21.39	13.98	7.00	12.00	18.00	28.00	39.00	11,438
Share of FDI	9.18	28.34	0.00	0.00	0.00	0.00	1.00	11,438

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

Table 1 Continued: Descriptive Statistics: Manufacturing sector

	Mean	sd	p10	p25	p50	p75	p90	N
Change 2008-2013								
ICT variables								
ΔShare of labor that uses computers	-2.55	38.95	-60.00	-15.00	0.00	11.00	40.00	11,438
ΔShare of labor that uses Internet	0.01	36.15	-50.00	-10.00	0.00	12.00	40.00	11,438
Δln(Stock of computer equipment/worker)	0.11	1.50	-1.69	-0.64	0.19	0.92	1.84	11,438
Employment and wages								
Δln(Number of white-collar workers)	0.03	0.81	-0.92	-0.41	0.00	0.47	1.01	11,438
Δln(Number of blue-collar worker)	-0.02	0.75	-0.86	-0.36	0.00	0.35	0.80	11,438
Δln(Annual real wage white-collar workers)	0.02	0.72	-0.86	-0.41	0.01	0.45	0.93	11,438
Δln(Annual real wage blue-collar workers)	0.04	0.59	-0.66	-0.30	0.03	0.37	0.76	11,438
ΔWhite/Blue-collar workers	1.21	22.81	-22.12	-8.05	0.23	9.88	25.83	11,438
ΔWhite/Blue-collar wages	0.01	0.23	-0.22	-0.08	0.00	0.10	0.26	11,438
Firm characteristics								
Δln(Capital/worker)	0.18	1.49	-1.49	-0.47	0.23	0.92	1.78	11,438
Δln(Total employment)	0.01	0.64	-0.69	-0.29	0.02	0.31	0.71	11,438

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

Table 2: Descriptive Statistics: Services sector

	Mean	sd	p10	p25	p50	p75	p90	N
2008								
ICT variables								
Share of labor that uses computers	27.47	34.74	0.00	0.00	10.00	50.00	90.00	6,241
Share of labor that uses Internet	22.56	31.15	0.00	0.00	9.00	33.00	80.00	6,241
Stock of computer equipment/worker	7.35	53.48	0.00	0.24	1.25	4.37	13.08	6,241
Employment and wages								
Number of white-collar workers	23.08	100.58	2.00	3.00	6.00	14.00	39.00	6,241
Number of blue-collar workers	119.77	1853.09	10.00	15.00	29.00	71.00	190.00	6,241
Annual real wage white-collar workers	119.11	159.62	27.00	48.00	80.25	140.00	236.17	6,241
Annual real wage blue-collar workers	67.22	74.59	19.20	29.78	48.00	78.47	127.40	6,241
White/Blue-collar workers	0.25	0.23	0.05	0.09	0.18	0.33	0.57	6,241
White/Blue-collar wages	2.01	1.48	0.63	1.00	1.56	2.58	4.10	6,241
Firm characteristics								
Capital/worker	214.10	507.08	0.56	10.06	66.72	243.09	545.45	6,241
Total employment	149.03	1883.58	14.00	21.00	39.00	95.00	248.00	6,241
Firm age	23.78	18.13	9.00	12.00	19.00	28.00	43.00	6,241
Share of FDI	3.75	17.66	0.00	0.00	0.00	0.00	0.00	6,241
2013								
ICT variables								
Share of labor that uses computer	34.06	35.97	0.00	1.00	20.00	60.00	100.00	6,241
Share of labor that uses Internet	32.68	35.48	0.00	1.00	20.00	58.00	100.00	6,241
Stock of computer equipment/worker	11.02	75.50	0.02	0.38	1.67	6.06	17.47	6,241
Employment and wages								
Number of white-collar workers	32.96	418.77	1.00	3.00	6.00	15.00	40.00	6,241
Number of blue-collar workers	132.75	1974.33	9.00	14.00	29.00	76.00	210.00	6,241
Annual real wage white-collar workers	91.23	90.41	25.64	39.98	67.38	109.61	177.44	6,241
Annual real wage blue-collar workers	60.05	58.50	20.11	28.42	42.95	69.49	116.28	6,241
White/Blue-collar workers	0.25	0.23	0.05	0.09	0.17	0.32	0.56	6,241
White/Blue-collar wages	1.83	1.35	0.63	0.99	1.41	2.31	3.69	6,241
Firm characteristics								
Capital/worker	247.03	787.23	0.64	13.03	71.93	257.57	609.07	6,241
Total employment	174.09	2175.95	14.00	21.00	40.00	105.00	283.00	6,241
Firm age	21.46	15.27	7.00	11.00	18.00	26.00	42.00	6,241
Share of FDI	4.53	20.09	0.00	0.00	0.00	0.00	0.00	6,241

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

Table 2 Continued: Descriptive Statistics: Services sector

	Mean	sd	p10	p25	p50	p75	p90	N
Change 2008-2013								
ICT variables								
ΔShare of labor that uses computers	6.60	40.43	-40.00	-5.00	0.00	20.00	70.00	6,241
ΔShare of labor that uses Internet	10.12	38.60	-30.00	0.00	0.00	23.00	70.00	6,241
Δln(Stock of computer equipment/worker)	0.03	1.60	-1.96	-0.78	0.13	0.95	1.95	6,241
Employment and wages								
Δln(Number of white-collar workers)	0.00	1.01	-1.10	-0.56	0.00	0.51	1.19	6,241
Δln(Number of blue-collar workers)	0.01	0.86	-0.83	-0.36	0.00	0.37	0.90	6,241
Δln(Annual real wage white-collar workers)	-0.18	1.01	-1.49	-0.76	-0.13	0.43	1.01	6,241
Δln(Annual real wage blue-collar workers)	-0.06	0.82	-1.00	-0.49	-0.06	0.35	0.90	6,241
ΔWhite/Blue-collar workers	0.00	0.27	-0.28	-0.10	0.00	0.09	0.26	6,241
ΔWhite/Blue-collar wages	-0.18	1.86	-2.40	-1.04	-0.09	0.71	1.82	6,241
Firm characteristics								
Δln(Capital/worker)	0.11	1.85	-2.00	-0.77	0.14	0.99	2.22	6,241
Δln(Total employment)	0.03	0.65	-0.62	-0.27	0.00	0.32	0.73	6,241

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

Table 3: Descriptive Statistics: Commerce sector

	Mean	sd	p10	p25	p50	p75	p90	N
2008								
ICT variables								
Share of labor that uses computers	18.89	33.25	0.00	0.00	0.00	25.00	85.00	8,333
Share of labor that uses Internet	14.38	27.78	0.00	0.00	0.00	15.00	60.00	8,333
Stock of computer equipment/worker	9.99	36.62	0.11	1.37	4.06	9.35	19.60	8,333
Employment and wages								
Number of white-collar workers	8.63	16.90	2.00	3.00	4.00	9.00	17.00	8,333
Number of blue-collar workers	24.02	32.85	7.00	10.00	16.00	25.00	45.00	8,333
Annual real wage white-collar workers	94.47	78.30	31.33	48.75	73.67	118.00	164.00	8,333
Annual real wage blue-collar workers	55.61	43.32	22.39	31.44	45.43	63.60	95.33	8,333
White/Blue-collar workers	0.32	0.25	0.09	0.15	0.25	0.42	0.67	8,333
White/Blue-collar wages	1.90	1.18	0.80	1.08	1.63	2.40	3.29	8,333
Firm characteristics								
Capital/worker	149.30	375.16	6.31	22.78	67.18	160.86	329.33	8,333
Total employment	34.74	45.57	13.00	16.00	22.00	35.00	62.00	8,333
Firm age	21.35	14.25	8.00	12.00	18.00	26.00	38.00	8,333
Share of FDI	1.86	13.12	0.00	0.00	0.00	0.00	0.00	8,333
2013								
ICT variables								
Share of labor that uses computers	44.68	42.08	0.00	0.00	30.00	95.00	100.00	8,333
Share of labor that uses Internet	42.30	41.54	0.00	0.00	30.00	90.00	100.00	8,333
Stock of computer equipment/worker	28.66	401.15	0.08	1.31	4.71	10.92	25.50	8,333
Employment and wages								
Number of white-collar workers	9.35	19.70	2.00	3.00	5.00	9.00	18.00	8,333
Number of blue-collar workers	24.63	33.11	7.00	10.00	15.00	26.00	48.00	8,333
Annual real wage white-collar workers	113.52	298.11	31.50	47.98	75.83	118.29	165.44	8,333
Annual real wage blue-collar workers	53.59	57.03	21.71	28.13	39.71	61.69	92.53	8,333
White/Blue-collar workers	0.32	0.24	0.09	0.15	0.24	0.41	0.67	8,333
White/Blue-collar wages	2.10	1.35	0.85	1.18	1.75	2.60	3.92	8,333
Firm characteristics								
Capital/worker	271.57	2139.37	2.83	25.45	79.27	200.13	429.00	8,333
Total employment	37.30	47.17	13.00	16.00	22.00	39.00	71.00	8,333
Firm age	19.70	13.24	7.00	10.00	17.00	26.00	36.00	8,333
Share of FDI	2.41	14.74	0.00	0.00	0.00	0.00	0.00	8,333

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

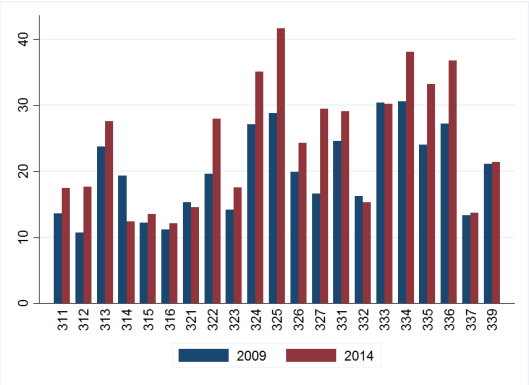
Table 3 Continued: Descriptive Statistics: Commerce sector

	Mean	sd	p10	p25	p50	p75	p90	N
Change 2008-2013								
ICT variables								
ΔShare of labor that uses computers	25.79	48.82	-20.00	0.00	5.00	70.00	100.00	8,333
ΔShare of labor that uses Internet	27.92	45.97	-10.00	0.00	10.00	70.00	100.00	8,333
Δln(Stock of computer equipment/worker)	-0.17	1.84	-2.46	-0.84	0.12	0.86	1.77	8,333
Employment and wages								
Δln(Number of white-collar workers)	0.03	0.82	-0.92	-0.41	0.00	0.41	1.10	8,333
Δln(Number of blue-collar workers)	0.01	0.66	-0.69	-0.29	0.00	0.31	0.75	8,333
Δln(Annual real wage white-collar workers)	0.02	0.81	-0.93	-0.42	-0.02	0.47	1.02	8,333
Δln(Annual real wage blue-collar workers)	-0.05	0.68	-0.81	-0.45	-0.06	0.32	0.78	8,333
ΔWhite/Blue-collar workers	0.00	0.26	-0.28	-0.10	0.00	0.10	0.29	8,333
ΔWhite/Blue-collar wages	0.20	1.63	-1.50	-0.58	0.13	0.97	2.01	8,333
Firm characteristics								
Δln(Capital/worker)	0.09	1.71	-1.80	-0.78	0.13	0.87	1.90	8,333
Δln(Total employment)	0.04	0.52	-0.51	-0.20	0.00	0.27	0.62	8,333

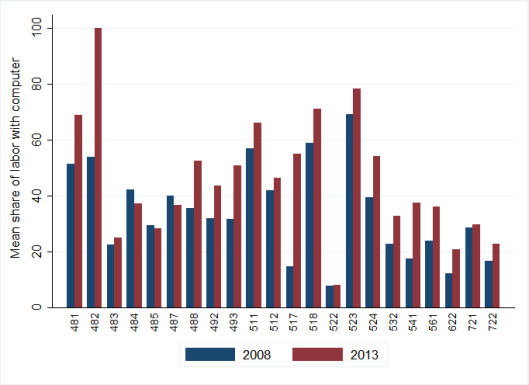
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI

Figure 3: ICT use: share of labor that uses computers by NAICS code

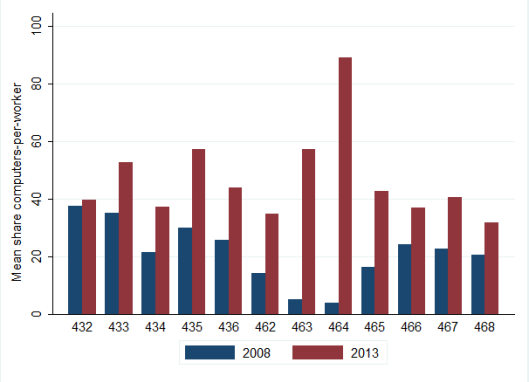
(a) *Manufacturing*



(b) *Services*



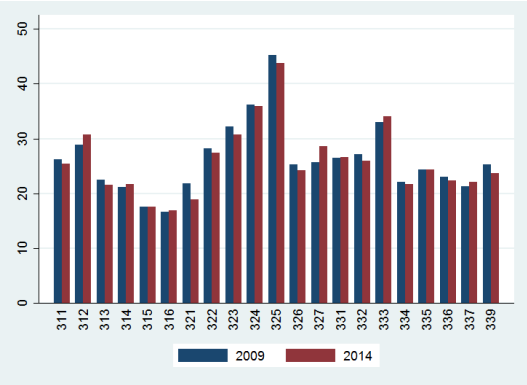
(c) *Commerce*



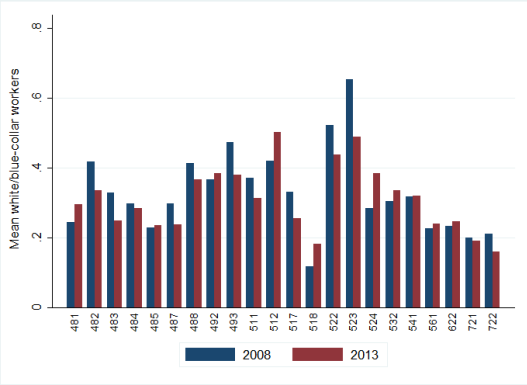
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure 4: Average Labor ratio by NAICS code

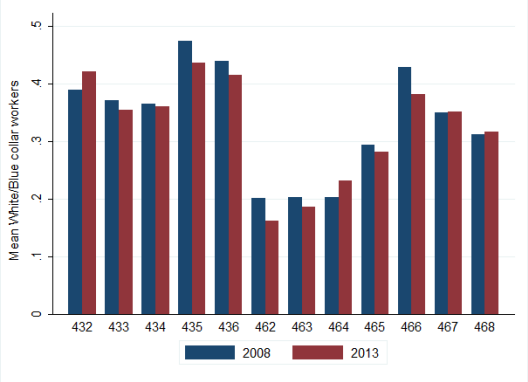
(a) *Manufacturing*



(b) *Services*



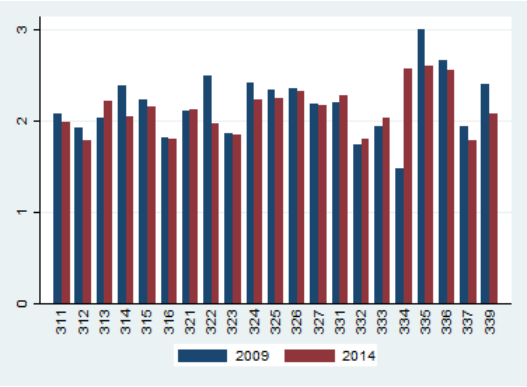
(c) *Commerce*



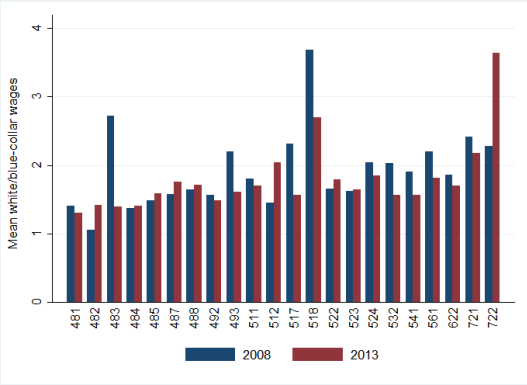
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure 5: Average Wage gap by NAICS code

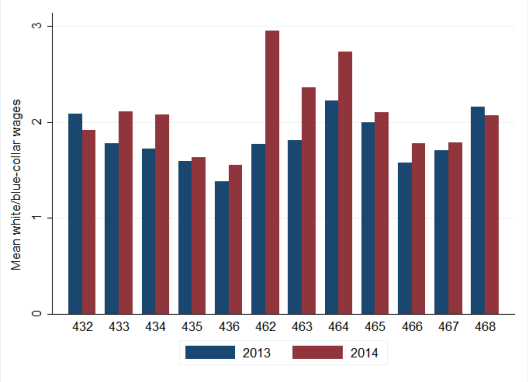
(a) *Manufacturing*



(b) *Services*



(c) *Commerce*

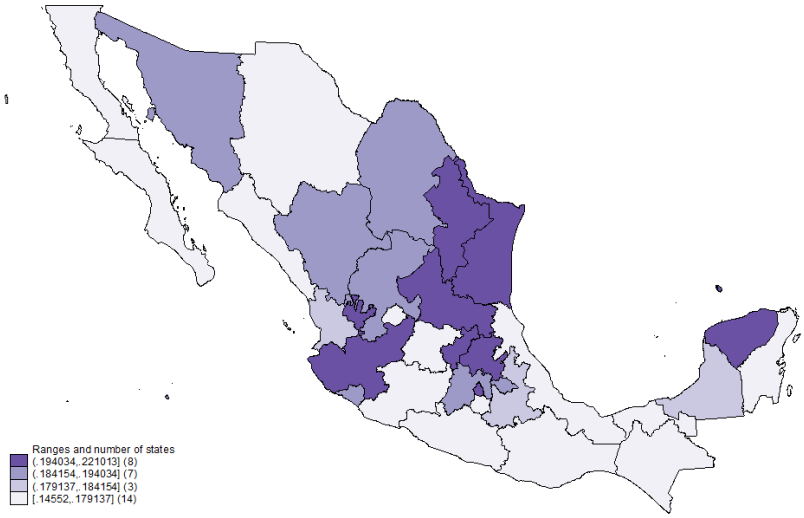


Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure 6: Average Labor ratios by state: Manufacturing

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

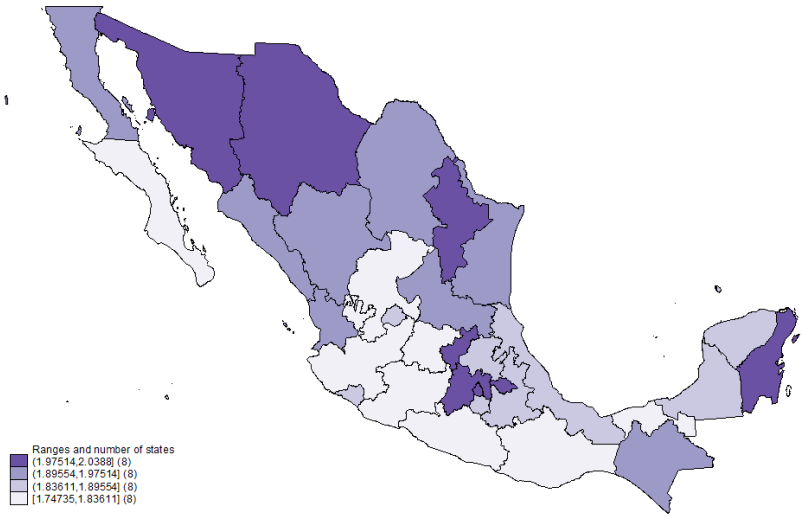
(b) *Number of white/blue-collar workers 2013*



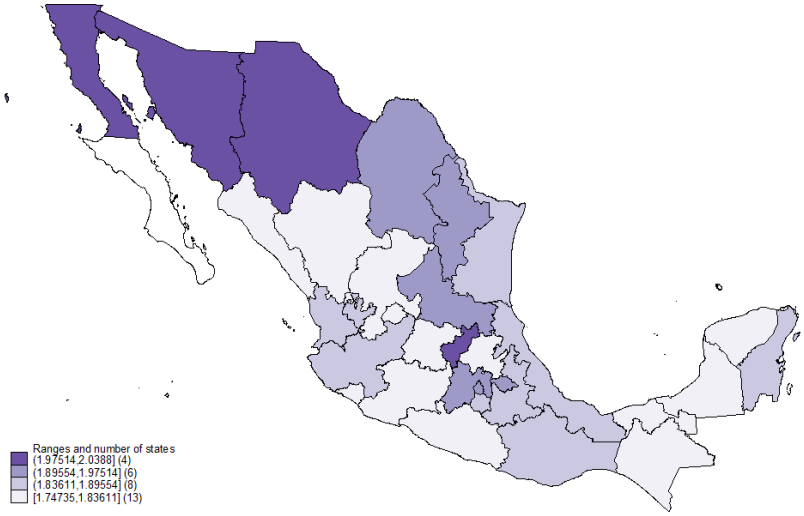
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure 7: Average Wage gap by state: Manufacturing

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



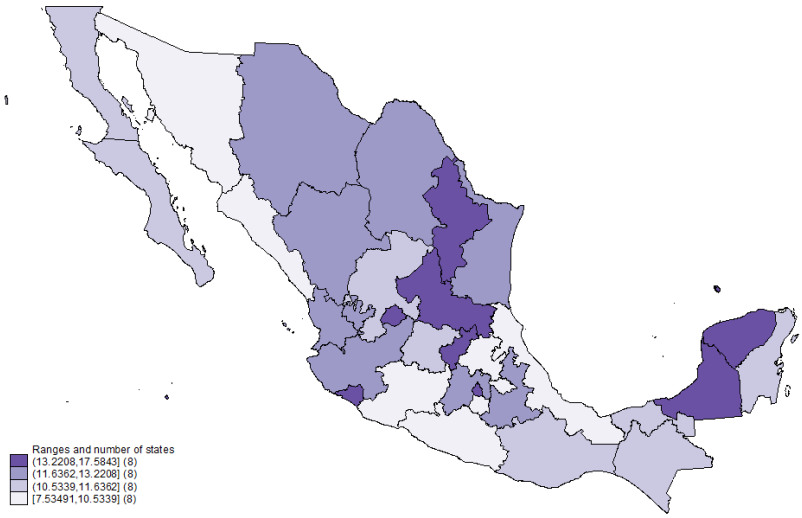
(b) *Wage gap of white/blue-collar workers 2013*



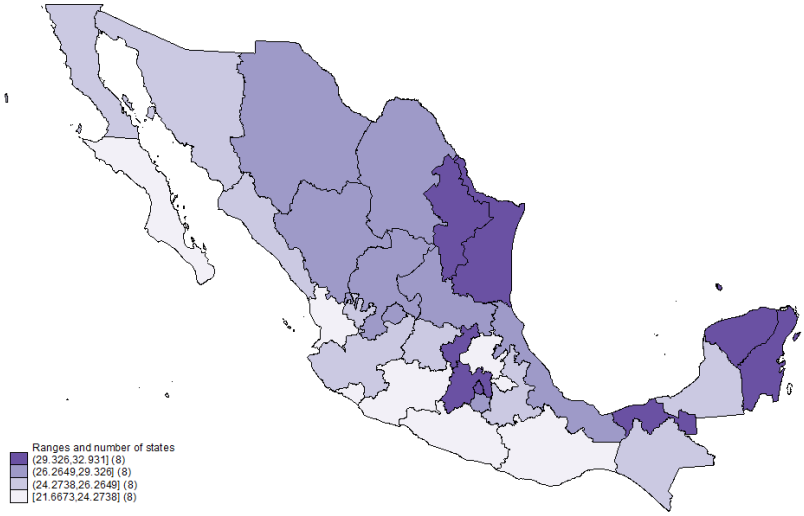
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure 8: ICT use by state: Manufacturing

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



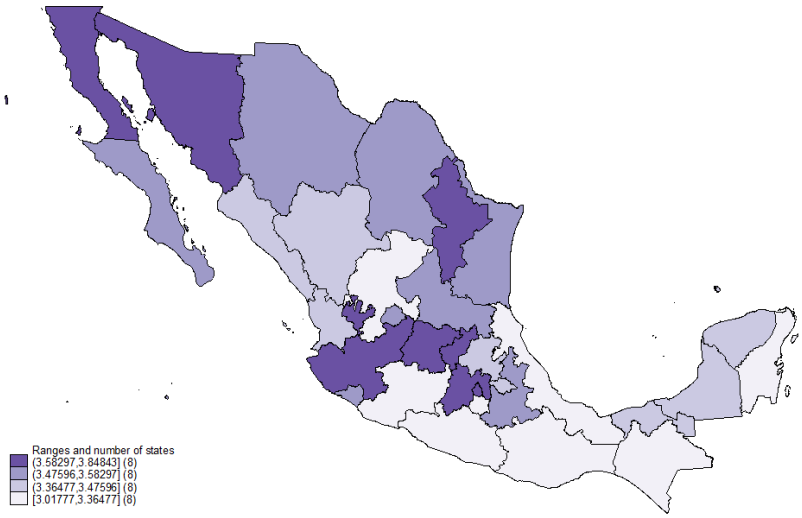
(b) *Share of labor that uses computers 2013*



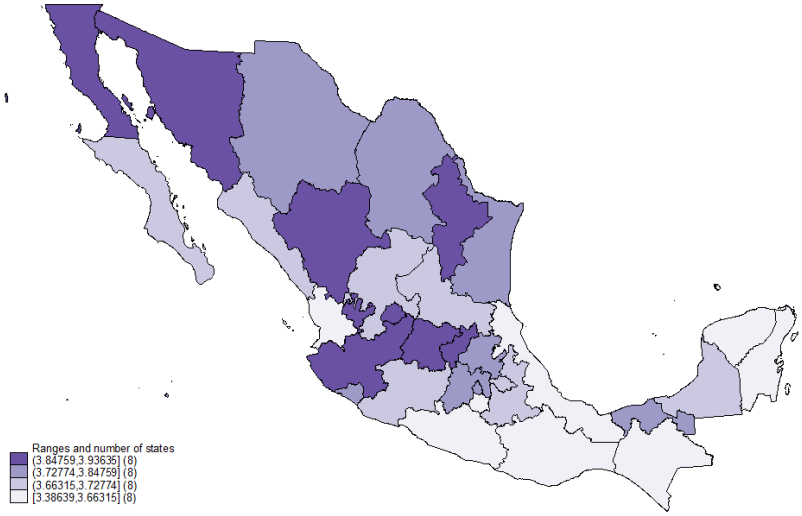
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure 9: TFP by state: Manufacturing

(a) *TFP index 2008*



(b) *TFP index 2013*



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

5 Results

5.1 ICT use, labor demand and wages

5.1.1 Manufacturing

Table 4 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 3.5% 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 worker is vulnerable to being substituted by a more intensive use of ICT.

When we analyze the corresponding wages for these two groups in Table 5 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 3.5% increase in white-collar wages and a 2.4% 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 negative.

When we use an instrumental variable approach to take into consideration 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 7. 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 and statistically significant in most of the specifications for the share of labor with computer and the share of labor with Internet but the coefficients are much lower than the ones observed for white-collar workers, 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 9), we observe that it exhibits significant increases in all of the specifications. Additionally, 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 white/blue-collar workers. This means that if an establishment changes from not using ICT to a 100% share of workers that use computers, this would translate into a change of 0.24 in the share of white/blue-collar workers, a value that is similar to the mean of this variable for 2013.

Once again, when we use wages of each type of worker as a dependent variable (Table 8), 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 9), we find that the coefficients are negative and significant in most of the specifications 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 0.24, which is equivalent to around 8% of the difference between the 10th and the 90th percentile of this variable.

Table 4: OLS estimates of the effect of ICT use on the Number of workers: Manufacturing

	(1)	(2)
Dependent variable: Δln(Number of white-collar workers)		
ΔShare of labor that uses computers	0.0010***	0.0010***
	(0.0002)	(0.0002)
ΔShare of labor that uses Internet	0.0012***	0.0013***
	(0.0002)	(0.0002)
Δln(stock of computer equipment/worker)	-0.0246***	-0.0170***
	(0.0056)	(0.0060)
Dependent variable: Δln(Number of blue-collar workers)		
ΔShare of labor that uses computers	-0.0002	-0.0001
	(0.0002)	(0.0002)
ΔShare of labor that uses Internet	-0.0003	-0.0001
	(0.0002)	(0.0002)
Δln(stock of computer equipment/worker)	-0.1179***	-0.0875***
	(0.0056)	(0.0058)
Controls		
Δln(capital/worker)	No	Yes
Observations	11,438	11,438

Robust standard errors in parentheses

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

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

Table 5: OLS estimates of the effect of ICT use on wages: Manufacturing

	(1)	(2)	(3)
Dependent variable: Δln(Wage of white-collar workers)			
ΔShare of labor that uses computers	0.0011***	0.0010***	0.0011***
	(0.0002)	(0.0002)	(0.0002)
ΔShare of labor that uses Internet	0.0011***	0.0011***	0.0011***
	(0.0002)	(0.0002)	(0.0002)
Δln(stock of computer equipment/worker)	0.0137***	0.0038	0.0034
	(0.0045)	(0.0049)	(0.0049)
Dependent variable: Δln(Wage of blue-collar workers)			
ΔShare of labor that uses computer	0.0007***	0.0007***	0.0007***
	(0.0001)	(0.0001)	(0.0001)
ΔShare of labor that uses Internet	0.0008***	0.0008***	0.0007***
	(0.0002)	(0.0002)	(0.0002)
Δln(stock of computer equipment/worker)	0.0299***	0.0173***	0.0169***
	(0.0037)	(0.0041)	(0.0040)
Controls			
Δln(capital/worker)	No	Yes	Yes
Age dummies	No	No	Yes
Size dummies	No	No	Yes
Observations	11,438	11,438	11,438

Standard errors in parentheses

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

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

Table 6: OLS estimates of the effect of ICT use on the share of white-collar/blue-collar workers and wages: Manufacturing

	(1)	(2)	(3)
Dependent variable: Δwhite/blue-collar workers			
ΔShare of labor that uses computers	0.0003***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)
ΔShare of labor that uses Internet	0.0003***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)
Δln(stock of computer equipment/worker)	0.0192***	0.0153***	0.0151***
	(0.0016)	(0.0017)	(0.0017)
Dependent variable: Δwhite/blue-collar wages			
ΔShare of labor that uses computers	0.0010**	0.0009**	0.0009**
	(0.0004)	(0.0005)	(0.0005)
ΔShare of labor that uses Internet	0.0010**	0.0010**	0.0012**
	(0.0005)	(0.0005)	(0.0005)
Δln(stock of computer equipment/worker)	-0.0400***	-0.0334***	-0.0322***
	(0.0110)	(0.0120)	(0.0119)
Controls			
Δln(capital/worker)	No	Yes	Yes
Age dummies	No	No	Yes
Size dummies	No	No	Yes
Observations	11,438	11,438	11,438

Standard errors in parentheses

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

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

Table 7: IV estimates of the effect of ICT use on the Number of workers: Manufacturing

	(1)	(2)
Dependent variable: Δln(Number of white-collar workers)		
ΔShare of labor that uses computers	0.0116***	0.0128***
	(0.0029)	(0.0031)
F- first stage	40.43	38.71
Sargan p-value	0.4598	0.4251
ΔShare of labor that uses Internet	0.0097***	0.0107***
	(0.0023)	(0.0023)
F- first stage	73.39	70.25
Sargan p-value	0.6130	0.5853
Δln(stock of computer equipment/worker)	0.3110***	0.5972***
	(0.0928)	(0.2041)
F- first stage	26.36	11.19
Sargan p-value	0.6596	0.7048
Dependent variable: Δln(Number of blue-collar workers)		
ΔShare of labor that uses computers	0.0039*	0.0080***
	(0.0022)	(0.0024)
F- first stage	40.43	38.71
Sargan p-value	0.1677	0.3352
ΔShare of labor that uses Internet	0.0029*	0.0063***
	(0.0017)	(0.0018)
F- first stage	73.39	70.25
Sargan p-value	0.1337	0.2164
Δln(stock of computer equipment/worker)	-0.0607	0.1139
	(0.0588)	(0.1209)
F- first stage	26.36	11.19
Sargan p-value	0.1856	0.1079
Controls		
ln(capital/worker)	No	Yes
Observations	11,438	11,438

Robust standard errors in parentheses

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

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

Table 8: IV estimates of the effect of ICT use on wages: Manufacturing

	(1)	(2)	(3)
Dependent variable: Δln(Wage of white-collar workers)			
ΔShare of labor that uses computers	0.0156***	0.0150***	0.0106***
	(0.0029)	(0.0029)	(0.0016)
F- first stage	40.43	38.71	106.26
Sargan p-value	0.1451	0.1527	0.1338
ΔShare of labor that uses Internet	0.0130***	0.0125***	0.0138***
	(0.0022)	(0.0022)	(0.0021)
F- first stage	73.39	70.25	73.93
Sargan p-value	0.2717	0.2869	0.1664
Δln(stock of computer equipment/worker)	0.4147***	0.6035***	0.9054***
	(0.0925)	(0.1872)	(0.3222)
F- first stage	26.36	11.19	6.69
Sargan p-value	0.1514	0.1241	0.1311
Dependent variable: Δln(Wage of blue-collar workers)			
ΔShare of labor that uses computer	0.0194***	0.0185***	0.0100***
	(0.0027)	(0.0027)	(0.0015)
F- first stage	40.43	38.71	106.26
Sargan p-value	0.5471	0. 4724	0.1468
ΔShare of labor that uses Internet	0.0225***	0.0216***	0.0157***
	(0.0033)	(0.0033)	(0.0026)
F- first stage	73.39	70.25	73.93
Sargan p-value	0.3492	0.3667	0.8176
Δln(stock of computer equipment/worker)	0.6351***	0.9118***	0.7571***
	(0.1110)	(0.2324)	(0.2563)
F- first stage	26.36	11.19	6.69
Sargan p-value	0.6448	0.2970	0.1273
Controls			
Δln(capital/worker)	No	Yes	Yes
Age dummies	No	No	Yes
Size dummies	No	No	Yes
Observations	11,438	11,438	11,438

Robust standard errors in parentheses

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

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

Table 9: IV estimates of the effect of ICT use on the share of white/blue-collar workers and wages: Manufacturing

	(1)	(2)
Dependent variable: Δwhite/blue-collar workers		
ΔShare of labor that uses computers	0.0024***	0.0018**
	(0.0008)	(0.0008)
F- first stage	40.43	38.71
Sargan p-value	0.8068	0.9983
ΔShare of labor that uses Internet	0.0018***	0.0014**
	(0.0006)	(0.0007)
F- first stage	73.39	70.25
Sargan p-value	0.1221	0.1475
Δln(stock of computer equipment/worker)	0.0785***	0.1211***
	(0.0230)	(0.0402)
F- first stage	26.34	11.11
Sargan p-value	0.4247	0.7757
Dependent variable: Δwhite/blue-collar wages		
ΔShare of labor that uses computer	-0.0239***	-0.0235***
	(0.0062)	(0.0063)
F- first stage	40.43	38.71
ΔShare of labor that uses Internet	-0.0201***	-0.0197***
	(0.0049)	(0.0050)
F- first stage	73.39	70.25
Sargan p-value	0.3811	0.3912
Δln(stock of computer equipment/worker)	-0.9751***	-1.8169***
	(0.2073)	(0.5389)
F- first stage	26.34	11.11
Sargan p-value	0.5499	0.9405
Controls		
Δln(capital/worker)	No	Yes
Observations	11,438	11,438

Robust standard errors in parentheses

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

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

5.1.2 Services and commerce

Tables 10, 11, and 12 show the results of the analysis of our main outcome variables for the services and commerce sectors. As the first table shows, the results for the number of white-collar workers indicate that though increases are observed in both sectors as a result of increasing adoption of ICT, the magnitudes are much lower than the ones observed for manufacturing, especially for commerce. Increases in the number of blue-collar workers in the services sector are higher than those of manufacturing, while commerce exhibits very low and even non-significant coefficients in some of the specifications. Consistent with these results, for services and commerce no significant changes in the ratio of white/blue-collar workers are observed.

On the other hand, contrary to what we observe for manufacturing, wages decrease for both groups in the services sector but this reduction is higher for white-collar workers, therefore decreasing the wage gap between both groups. In this case, a 10 percentage point increase in the share of labor that uses computers is associated with a reduction of 0.24 in the wage gap between the two types of worker. This value is exactly the same as the one observed for manufacturing though the dynamics differ between these two sectors. These differences against the manufacturing sector could be explained by the fact that services appear to be comparatively more in risk of automation (though, as mentioned by Frey et al. (2016), not necessarily automated) than manufacturing (World Bank, 2016). Therefore, as routine and non-routine tasks within this sector could be automated, this reduces the skill-value of both white and blue-collar workers that currently perform these tasks, but the effect is higher on white-collar workers, therefore, reducing the wage gap.

For the commerce sector, the results regarding wages indicate that in some specifications, wages of white-collar workers appear to increase as a result of ICT adoption. On the other hand, negative effects over blue-collar wages are observed. Therefore, the wage gap between white and blue-collar workers increases. Although this sector also faces a higher risk of automation as explained in World Bank (2016), in this case the wage reduction affects blue-collar workers while the wages of white-collar workers do not change significantly. Though there is no evidence of reductions in the number of blue-collar workers for this sector (which would mean that these workers are being substituted by technology), the wage reduction could indicate that these kinds of workers are performing simpler (less valuable) tasks as the use of technologies allows to at least partially automate some processes.

Table 10: IV estimates of the effect of ICT use on the Number of workers: Services and Commerce

	Services		Commerce	
	(1)	(2)	(3)	(4)
Dependent variable: Δln(Number of white-collar workers)				
ΔShare of labor that uses computers	0.0068***	0.0075***	0.0013***	0.0012***
	(0.0025)	(0.0026)	(0.0003)	(0.0003)
F- first stage	82.53	74.85	1,067.39	1,038.03
Sargan p-value	0.7409	0.8255	0.6321	0.7069
ΔShare of labor that uses Internet	0.0063***	0.0070***	0.0012***	0.0012***
	(0.0024)	(0.0025)	(0.0003)	(0.0003)
F- first stage	98.06	89.27	1429.109	1455.34
Sargan p-value	0.4656	0.5104	0.6929	0.7764
Δln(stock of computer equipment/worker)	0.1575**	0.2297**	0.2404***	0.4014***
	(0.0694)	(0.0968)	(0.0711)	(0.1406)
F- first stage	88.88	52.73	30.77	12.45
Sargan p-value	0.9345	0.9580	0.9070	0.5607
Dependent variable: Δln(Number of blue-collar workers)				
ΔShare of labor that uses computers	0.0091***	0.0111***	0.0005	0.0006*
	(0.0023)	(0.0025)	(0.0003)	(0.0003)
F- first stage	82.53	74.85	1,067.39	1,038.03
Sargan p-value	0.4257	0.2925	0.2142	0.1426
ΔShare of labor that uses Internet	0.0088***	0.0107***	0.0003	0.0006**
	(0.0022)	(0.0023)	(0.0003)	(0.0003)
F- first stage	98.06	89.27	1429.109	1455.34
Sargan p-value	0.7562	0.6342	0.1540	0.2451
Δln(stock of computer equipment/worker)	0.2088***	0.3306***	0.1150*	0.2667**
	(0.0550)	(0.0762)	(0.0659)	(0.1285)
F- first stage	88.88	52.73	30.77	12.45
Sargan p-value	0.2081	0.2207	0.9097	0.4628
Controls				
ln(capital/worker)	No	Yes	No	Yes
Observations	6,241	6,241	8,333	8,333

Robust standard errors in parentheses

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

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

Table 11: IV estimates of the effect of ICT use on Wages: Services and Commerce

	Services		Commerce	
	(1)	(2)	(3)	(4)
Dependent variable: Δ ln(Wages of white-collar workers)				
ΔShare of labor that uses computers	-0.0263***	-0.0308***	0.0000	0.0011
	(0.0029)	(0.0065)	(0.0004)	(0.0007)
F- first stage	82.53	21.79	1,067.39	248.45
Sargan p-value	0.6023	0.2424	0.1799	0.2324
ΔShare of labor that uses Internet	-0.0250***	-0.0509***	0.0000	0.0011*
	(0.0026)	(0.0136)	(0.0004)	(0.0007)
F- first stage	98.06	9.56	1429.109	301.285
Sargan p-value	0.6083	0.9829	0.1800	0.2380
Δln(stock of computer equipment/worker)	-0.6635***	-0.7686***	0.1423**	-1.1797***
	(0.0755)	(0.1337)	(0.0655)	(0.4162)
F- first stage	88.88	31.72	30.77	5.63
Sargan p-value	0.9545	0.4930	0.2074	0.7652
Dependent variable: Δ ln(Wages of blue-collar workers)				
ΔShare of labor that uses computers	-0.0104***	-0.0191***	-0.0023***	-0.0007
	(0.0021)	(0.0053)	(0.0004)	(0.0006)
F- first stage	82.53	21.79	1,067.39	248.45
Sargan p-value	0.1567	0.9491	0.1426	0.2411
ΔShare of labor that uses Internet	-0.0101***	-0.0206***	-0.0021***	-0.0007
	(0.0019)	(0.0071)	(0.0003)	(0.0005)
F- first stage	98.06	9.56	1429.109	301.285
Sargan p-value	0.3960	0.2520	0.1330	0.2363
ln(stock of computer equipment/worker)	-0.2563***	-0.3523***	-0.4000***	0.0379
	(0.0493)	(0.0876)	(0.0871)	(0.1254)
F- first stage	88.88	31.72	30.77	5.63
Sargan p-value	0.4801	0.6543	0.8237	0.2851
Controls				
ln(capital/worker)	No	Yes	No	Yes
Age dummies	No	Yes	No	Yes
Size dummies	No	Yes	No	Yes
Observations	6,241	6,241	8,333	8,333

Robust standard errors in parentheses

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

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

Table 12: IV estimates of the effect of ICT use on white/blue-collar workers and wages: Services and Commerce

	Services		Commerce	
	(1)	(2)	(3)	(4)
Dependent variable: Δwhite/blue-collar workers				
ΔShare of labor that uses computers	-0.0000	0.0003	0.0001	0.0001
	(0.0008)	(0.0013)	(0.0001)	(0.0001)
F- first stage	82.53	21.79	1,067.39	248.45
Sargan p-value	0.9323	0.8237	0.6712	0.8552
ΔShare of labor that uses Internet	0.0002	0.0010	0.0001	0.0001
	(0.0006)	(0.0016)	(0.0001)	(0.0002)
F- first stage	98.06	9.56	1429.109	301.285
Sargan p-value	0.2055	0.1426	0.3203	0.2434
Δln(stock of computer equipment/worker)	0.0032	0.0156	0.0135	-0.0335
	(0.0178)	(0.0300)	(0.0242)	(0.0396)
F- first stage	88.88	31.72	30.77	5.63
Sargan p-value	0.2881	0.2442	0.6094	0.8005
Dependent variable: Δwhite/blue-collar wages				
ΔShare of labor that uses computers	-0.0227***	-0.0237**	0.0075***	0.0039***
	(0.0047)	(0.0095)	(0.0007)	(0.0013)
F- first stage	82.53	21.79	1,067.39	248.45
Sargan p-value	0.5215	0.8502	0.1527	0.2072
ΔShare of labor that uses Internet	-0.0201***	-0.0303**	0.0069***	0.0038***
	(0.0041)	(0.0133)	(0.0007)	(0.0013)
F- first stage	98.06	9.56	1429.109	301.285
Sargan p-value	0.3771	0.5095	0.1694	0.2227
Δln(stock of computer equipment/worker)	-0.6464***	-0.3818**	1.3305***	-2.0795***
	(0.1219)	(0.1604)	(0.2244)	(0.5474)
F- first stage	88.88	31.72	30.77	5.63
Sargan p-value	0.3011	0.2424	0.1642	0.3015
Controls				
Δln(capital/worker)	No	Yes	No	Yes
Age dummies	No	Yes	No	Yes
Size dummies	No	Yes	No	Yes
Observations	6,241	6,241	8,333	8,333

Robust standard errors in parentheses

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

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

5.2 ICT use and TFP

As 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.

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

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 for the manufacturing sector are shown in Table 13 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 an 18% increase in productivity. This result is consistent with what Iacovone et al. (2016) found using a much smaller sample of big firms and a different proxy for performance (sales-per-worker). As Table 14 shows, the results for the services sector are similar but in the case of commerce, the effects are not robust across specifications.

Table 13: IV estimates of the effect of ICT use on TFP: Manufacturing

	(1)	(2)	(3)
Dependent variable: Δln(TFP)			
ΔShare of labor that uses computer	0.0152***	0.0293***	0.0186***
	(0.0055)	(0.0062)	(0.0034)
F- first stage	40.43	38.71	106.26
Sargan p-value	0.9763	0.6905	0.7873
ΔShare of labor that uses Internet	0.0118***	0.0230***	0.0245***
	(0.0041)	(0.0045)	(0.0047)
F- first stage	73.39	70.25	73.93
Sargan p-value	0.7783	0.8617	0.9825
Δln(stock of computer equipment/worker)	0.2606**	1.2524***	2.7092**
	(0.1159)	(0.3934)	(1.3048)
F- first stage	26.34	11.11	6.69
Sargan p-value	0.5403	0.2944	0.5170
Controls			
Δln(capital/worker)	No	Yes	Yes
Age dummies	No	No	Yes
Size dummies	No	No	Yes
Observations	11,438	11,438	11,438

Robust standard errors in parentheses

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

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

Table 14: IV estimates of the effect of ICT use on TFP: Services and Commerce

	(1)	(2)	(3)	(4)	(5)	(6)
	Services			Commerce		
Dependent variable: Δln(TFP)						
ΔShare of labor that uses computer	0.0080**	0.0178***	0.0274***	-0.0036***	-0.0011	0.0059***
	(0.0038)	(0.0045)	(0.0100)	(0.0008)	(0.0008)	(0.0006)
F- first stage	38.79	34.12	8.95	602.23	584.23	598.79
Sargan p-value	0.1345	0.5700	0.9562	0.3255	0.5137	0.5478
ΔShare of labor that uses Internet	0.0052**	0.0146***	0.0096**	-0.0013**	-0.0002	0.0058***
	(0.0024)	(0.0037)	(0.0046)	(0.0005)	(0.0005)	(0.0006)
F- first stage	103.31	51.28	32.50	1251.50	1230.77	668.52
Sargan p-value	0.8628	0.2706	0.1693	0.2199	0.2833	0.6092
Δln(stock of computer equipment/worker)	0.2834***	0.7115***	0.7792***	-0.2994**	-0.0340	-3.2149
	(0.1020)	(0.1704)	(0.2448)	(0.1272)	(0.1733)	(2.1184)
F- first stage	49.81	31.42	16.92	20.00	10.92	1.37
Sargan p-value	0.4660	0.4959	0.3778	0.1900	0.2703	0.1208
Controls						
Δln(capital/worker)	No	Yes	Yes	No	Yes	Yes
Age dummies	No	No	Yes	No	No	Yes
Size dummies	No	No	Yes	No	No	Yes
Observations	6,241	6,241	6,241	8,333	8,333	8,333

Robust standard errors in parentheses

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

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

5.3 ICT use and other firm-level outcomes

When we analyze the relation between other firm-level outcomes and ICT adoption as shown in Table 15, the results are very robust across specifications for the manufacturing industry. An increase in ICT use is associated with firm-level growth in terms of the total number of employees, which is consistent with previous results regarding the number of white-collar and blue-collar workers in absolute terms.

Similar results are observed when we analyze the effect of ICT use on labor productivity proxies such as sales-per-worker and value-added-per worker. In this case, a 10 percentage point increase in the share of labor that uses computers, yields a 17% increase in any of these two variables.

As Table 16 shows, the results for services are similar when we analyze increases in the size of the establishment. However, for sales-per-worker and value-added-per-worker, even though the coefficients are statistically significant, the magnitudes are much lower in comparison with the manufacturing sector. In the case of commerce, as shown in Table 17, the results are even lower for firm size and sales-per-worker. For value-added-per-worker, the magnitudes are similar to the ones observed for services.

Table 15: IV estimates of the effect of ICT use on other outcomes: Manufacturing

	Δln(number of workers)		Δln(sales-per-worker)			Δln(Value added-per-worker)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔShare of labor that uses computer	0.0084***	0.0123***	0.0438***	0.0403***	0.0166***	0.0425***	0.0392***	0.0170***
	(0.0020)	(0.0023)	(0.0052)	(0.0050)	(0.0019)	(0.0053)	(0.0051)	(0.0020)
F- first stage	40.43	38.71	40.43	38.71	106.26	40.43	38.71	106.26
Sargan p-value	0.4137	0.2936	0.1546	0.1742	0.2502	0.1762	0.1681	0.3080
ΔShare of labor that uses Internet	0.0070***	0.0102***	0.0363***	0.0333***	0.0216***	0.0341***	0.0314***	0.0220***
	(0.0016)	(0.0017)	(0.0035)	(0.0033)	(0.0026)	(0.0034)	(0.0033)	(0.0028)
F-first stage	73.39	70.25	73.39	70.25	73.93	73.39	70.25	73.93
Sargan p-value	0.5762	0.4487	0.3640	0.4110	0.3865	0.2352	0.2604	0.1884
Δln(stock of computer equipment/worker)	0.3553***	0.2527**	1.3811***	2.3675***	1.9703***	1.3042***	2.1288***	2.1130***
	(0.1080)	(0.1181)	(0.1948)	(0.5891)	(0.5887)	(0.1879)	(0.5256)	(0.6284)
F-first stage	26.34	11.11	26.34	11.11	6.69	26.34	11.11	6.69
Sargan p-value	0.4106	0.6836	0.6361	0.9283	0.1110	0.6682	0.6002	0.3160
Controls								
Δln(capital/worker)	No	Yes	No	Yes	Yes	No	Yes	Yes
Age dummies	No	No	No	No	Yes	No	No	Yes
Size dummies	No	No	No	No	Yes	No	No	Yes
Observations	11,438	11,438	11,438	11,438	11,438	11,438	11,438	11,438

Standard errors in parentheses

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

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

Table 16: IV estimates of the effect of ICT use on other outcomes: Services

	Δln(number of workers)		Δln(sales-per-worker)			Δln(Value added-per-worker)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔShare of labor that uses computer	0.0105***	0.0129***	0.0114***	0.0083***	0.0082*	0.0076***	0.0051**	0.0079*
	(0.0018)	(0.0019)	(0.0024)	(0.0024)	(0.0048)	(0.0022)	(0.0022)	(0.0047)
F- first stage	72.68	65.53	72.68	65.53	14.45	72.68	65.53	14.45
Sargan p-value	0.2512	0.4402	0.1576	0.1417	0.1316	0.1532	0.3116	0.3155
ΔShare of labor that uses Internet	0.0092***	0.0111***	0.0086***	0.0070***	0.0098*	0.0065***	0.0050***	0.0112**
	(0.0015)	(0.0017)	(0.0017)	(0.0017)	(0.0051)	(0.0016)	(0.0016)	(0.0051)
F-first stage	148.63	142.38	148.63	142.38	16.80	148.63	142.38	16.80
Sargan p-value	0.6603	0.8653	0.1610	0.6076	0.4723	0.2147	0.6847	0.5288
Δln(stock of computer equipment/worker)	0.3003***	0.4844***	0.3197***	0.3094***	0.2430*	0.2515***	0.2305***	0.2615**
	(0.0549)	(0.0852)	(0.0640)	(0.0877)	(0.1247)	(0.0629)	(0.0859)	(0.1253)
F-first stage	58.04	38.91	58.04	38.91	19.39	58.04	38.91	19.39
Sargan p-value	0.4022	0.5239	0.2658	0.2583	0.2334	0.1356	0.1277	0.1139
Controls								
Δln(capital/worker)	No	Yes	No	Yes	Yes	No	Yes	Yes
Age dummies	No	No	No	No	Yes	No	No	Yes
Size dummies	No	No	No	No	Yes	No	No	Yes
Observations	6,241	6,241	6,241	6,241	6,241	6,241	6,241	6,241

Standard errors in parentheses

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

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

Table 17: IV estimates of the effect of ICT use on other outcomes: Commerce

	Δln(number of workers)		Δln(sales-per-worker)			Δln(Value added-per-worker)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔShare of labor that uses computer	0.0018***	0.0019***	0.0002	-0.0004	0.0040***	0.0089***	0.0085***	0.0109***
	(0.0002)	(0.0002)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0007)
F- first stage	1041.78	1008.71	1041.78	1008.71	576.59	1041.78	1008.71	576.59
Sargan p-value	0.8630	0.7107	0.4121	0.9509	0.4809	0.6244	0.9946	0.8315
ΔShare of labor that uses Internet	0.0016***	0.0018***	0.0002	-0.0004	0.0039***	0.0082***	0.0078***	0.0107***
	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0006)	(0.0005)	(0.0005)	(0.0007)
F-first stage	1395.40	1358.95	1395.40	1358.95	645.52	1395.40	1358.95	645.52
Sargan p-value	0.8749	0.7106	0.4124	0.9525	0.4453	0.6421	0.9530	0.7401
Δln(stock of computer equipment/worker)	0.3197***	0.6073***	0.0506	-0.1112	-1.8585*	1.6305***	2.7020***	-6.0131*
	(0.0639)	(0.1496)	(0.0841)	(0.1515)	(1.0491)	(0.2308)	(0.5890)	(3.2325)
F-first stage	28.66	12.32	28.66	12.32	2.11	28.66	12.32	2.11
Sargan p-value	0.1905	0.4532	0.2617	0.2060	0.0995	0.9982	0.8023	0.3185
Controls								
Δln(capital/worker)	No	Yes	No	Yes	Yes	No	Yes	Yes
Age dummies	No	No	No	No	Yes	No	No	Yes
Size dummies	No	No	No	No	Yes	No	No	Yes
Observations	8,333	8,333	8,333	8,333	8,333	8,333	8,333	8,333

Standard errors in parentheses

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

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

5.4 Robustness tests

To analyze the robustness of our results, we estimated the same OLS regressions in levels but without fixed effects to evaluate the sensitivity of our results to unobserved heterogeneity. Tables 18, 19 and 20 show these results for the manufacturing sector. The pooled regressions exhibit similar results to the ones of the initial OLS regressions 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.

Also, 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[7], we estimated the same models with a different set of instrumental variables in which we used information from Mexico's 1999 Economic Census to calculate ICT sectoral intensity. The results (not shown here) do not change much.

5.4.1 Heterogeneity of results by sales-per-worker increases

We estimate split regressions by change in sales-per-worker quartile over the share of labor that uses Internet. We choose this variable as it is the one that should be better instrumented using our IV. The purpose of this analysis is to test whether the effects of ICT adoption over our main outcome variables vary according to labor productivity growth. That is, we analyze whether higher-growth firms have different effects.

For the manufacturing sector (Table 21), we observe that for lower quartiles, there is an increase both in the number of white-collar workers and in the number of blue-collar workers. However, for higher quartiles, though we still observe some positive effects over white-collar workers, the number of blue-collar workers reduces, indicating a possible displacement of this type of workers due to increasing ICT adoption in this segment of firms. Accordingly, the ratio of white/blue-collar workers increases. Wages for both groups decrease for the lowest quartile, while increases are observed in the highest quartiles for both groups. However, similarly to our previous results, increases appear to be higher for blue-collar workers, leading to a reduction in the wage gap.

For services, increases in the use of ICT in the highest quartile are associated with a higher ratio of white/blue-collar workers, while negative or no significant effects are observed for lower quartiles of

[7]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.

labor productivity growth. The wage gap reduces for the highest quartile as wages for blue-collar workers increase, which is similar to what we observe on average for the manufacturing sector. However, for the lowest quartile though the wage ratio also reduces, this result is observed because wages for both white and blue-collar workers are declining but the later exhibit lower reductions.

In the commerce sector, increases in the number of both types of workers are observed for the lowest quartiles, while these figures decrease for the highest quartile. In terms of wages, the gap increases regardless of the growth quartile, though for the highest one, real wage increases are observed for both groups while for the lowest one reductions are observed especially for blue-collar. Therefore, the underlying mechanisms appear to vary by growth level.

The results for the highest growth quartiles of the manufacturing and services sectors are consistent with a rent-sharing mechanism that benefits both types of workers, but also with the idea that high-growth firms tend to adopt better practices, and to provide more training to their workers, allowing also for low-skilled workers to become more sophisticated.

Table 18: Pooled regression estimates of the effect of ICT use on the Number workers: Manufacturing

	(1)	(2)	(3)
Dependent variable: ln(Number of white-collar workers)			
Share of labor that uses computers	0.0088***	0.0084***	0.0094***
	(0.0003)	(0.0003)	(0.0002)
Share of labor that uses Internet	0.0077***	0.0073***	0.0087***
	(0.0003)	(0.0003)	(0.0003)
ln(stock of computer equipment/worker)	0.1773***	0.1450***	0.1253***
	(0.0077)	(0.0085)	(0.0076)
Dependent variable: ln(Number of blue-collar workers)			
Share of labor that uses computers	0.0045***	0.0046***	0.0056***
	(0.0003)	(0.0003)	(0.0002)
Share of labor that uses Internet	0.0033***	0.0034***	0.0048***
	(0.0003)	(0.0003)	(0.0003)
ln(stock of computer equipment/worker	-0.0455***	-0.0490***	-0.0567***
	(0.0069)	(0.0077)	(0.0069)
Controls			
ln(capital/worker)	No	Yes	Yes
Age dummies	No	No	Yes
Size dummies	No	No	Yes
Sectoral effects	No	No	Yes
Observations	22,876	22,876	22,876

Robust standard errors in parentheses

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

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

Table 19: Pooled regression estimates of the effect of ICT use on wages: Manufacturing

	(1)	(2)	(3)	(4)	(5)
Dependent variable: ln(Wage of white-collar workers)					
Share of labor that uses computer	0.0021***	0.0018***	0.0006***	0.0027***	0.0014***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share of labor that uses Internet	0.0017***	0.0014***	0.0005***	0.0024***	0.0013***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ln(stock of computer equipment/worker)	0.0792***	0.0488***	0.0438***	0.0380***	0.0360***
	(0.0037)	(0.0040)	(0.0035)	(0.0036)	(0.0033)
Dependent variable: ln(Wage of blue-collar workers)					
Share of labor that uses computer	0.0011***	0.0008***	0.0000	0.0015***	0.0008***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share of labor that uses Internet	0.0007***	0.0004***	-0.0001	0.0013***	0.0007***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ln(stock of computer equipment/worker)	0.0832***	0.0518***	0.0471***	0.0425***	0.0399***
	(0.0030)	(0.0032)	(0.0029)	(0.0029)	(0.0028)
Controls					
ln(capital/worker)	No	Yes	Yes	Yes	Yes
Age dummies	No	No	Yes	No	Yes
Size dummies	No	No	Yes	No	Yes
Sectoral effects	No	No	No	Yes	Yes
Observations	22,876	22,876	22,876	22,876	22,876

Robust standard errors in parentheses

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

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

Table 20: Pooled estimates of the effect of ICT use on regression share of white-collar/blue-collar workers and wages: Manufacturing

	(1)	(2)	(3)	(4)	(5)
Dependent variable: Number white/blue-collar workers					
Share of labor that uses computers	0.0009***	0.0009***	0.0010***	0.0009***	0.0010***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Share of labor that uses Internet	0.0009***	0.0009***	0.0010***	0.0008***	0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
ln(stock of computer equipment/worker)	0.0448***	0.0397***	0.0380***	0.0371***	0.0356***
	(0.0011)	(0.0013)	(0.0013)	(0.0012)	(0.0012)
Dependent variable: Wages white/blue-collar workers					
Share of labor that uses computers	0.0023***	0.0023***	0.0012***	0.0024***	0.0013***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Share of labor that uses Internet	0.0022***	0.0022***	0.0013***	0.0024***	0.0014***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
ln(stock of computer equipment/worker)	-0.0144**	-0.0098	-0.0092	-0.0136*	-0.0107
	(0.0068)	(0.0075)	(0.0073)	(0.0074)	(0.0074)
Controls					
ln(capital/worker)	No	Yes	Yes	Yes	Yes
Age dummies	No	No	Yes	No	Yes
Size dummies	No	No	Yes	No	Yes
Sectoral effects	No	No	No	Yes	Yes
Observations	22,876	22,876	22,876	22,876	22,876

Robust standard errors in parentheses

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

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

Table 21: IV estimates of the effect of the share of labor with Internet on labor outcomes by quartile of income-per-worker growth: Manufacturing

	1st quartile	2nd quartile	3rd quartile	4th quartile
Dependent variable: Δln(Number of white-collar workers)				
ΔShare of labor that uses Internet	0.0298***	0.0189**	0.0089**	-0.0011
	(0.0085)	(0.0074)	(0.0042)	(0.0026)
F- first stage	10.96	7.94	16.55	67.13
Sargan p-value	0.2230	0.8503	0.8674	0.6233
Dependent variable: Δln(Number of blue-collar workers)				
ΔShare of labor that uses Internet	0.0496***	0.0163***	-0.0070**	-0.0184***
	(0.0133)	(0.0060)	(0.0032)	(0.0030)
F- first stage	8.83	8.48	16.55	53.53
Sargan p-value	0.9703	0.4196	0.6502	0.8251
Dependent variable: Δln(Wage of white-collar workers)				
ΔShare of labor that uses Internet	-0.0209**	-0.0068	0.0166***	0.0283***
	(0.0081)	(0.0055)	(0.0047)	(0.0032)
F- first stage	8.83	8.48	16.55	67.28
Sargan p-value	0.1862	0.4234	0.6731	0.6110
Dependent variable: Δln(Wage of blue-collar workers)				
ΔShare of labor that uses Internet	-0.0331***	0.0082*	0.0216***	0.0292***
	(0.0093)	(0.0042)	(0.0045)	(0.0031)
F- first stage	8.83	8.48	16.55	67.12
Sargan p-value	0.5190	0.5803	0.5705	0.3109
Dependent variable:Δwhite/blue-collar workers				
ΔShare of labor that uses Internet	-0.2234	0.1585	0.4136***	0.2322***
	(0.2294)	(0.1476)	(0.1391)	(0.0743)
F- first stage	8.83	8.48	16.55	59.71
Sargan p-value	0.2196	0.8847	0.2659	0.7336
Dependent variable:Δwhite/blue-collar wages				
ΔShare of labor that uses Internet	0.0034	-0.0449**	-0.0313***	-0.0100*
	(0.0135)	(0.0184)	(0.0115)	(0.0052)
F- first stage	8.83	8.48	16.55	67.12
Sargan p-value	0.8468	0.2699	0.4443	0.7944
Observations	2,860	2,859	2,860	2,859

Robust standard errors in parentheses

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

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

Table 22: IV estimates of the effect of the share of labor with Internet on labor outcomes by quartile of income-per-worker growth: Services

	1st quartile	2nd quartile	3rd quartile	4th quartile
Dependent variable: Δln(Number of white-collar workers)				
ΔShare of labor that uses Internet	0.0171***	-0.0038	-0.0083*	0.0131***
	(0.0040)	(0.0047)	(0.0045)	(0.0035)
F- first stage	42.15	33.61	33.94	48.86
Sargan p-value	0.4166	0.2341	0.1015	0.5949
Dependent variable: Δln(Number of blue-collar workers)				
ΔShare of labor that uses Internet	0.0159***	0.0086***	0.0019	-0.0081**
	(0.0038)	(0.0033)	(0.0028)	(0.0035)
F- first stage	34.72	28.73	38.48	40.05
Sargan p-value	0.5867	0.2697	0.2203	0.1805
Dependent variable: Δln(Wage of white-collar workers)				
ΔShare of labor that uses Internet	-0.0522***	-0.0270***	-0.0183***	-0.0002
	(0.0055)	(0.0048)	(0.0062)	(0.0024)
F- first stage	41.04	33.61	9.62	55.71
Sargan p-value	0.6008	0.8138	0.1513	0.1110
Dependent variable: Δln(Wage of blue-collar workers)				
ΔShare of labor that uses Internet	-0.0362***	-0.0231***	-0.0007	0.0243***
	(0.0047)	(0.0044)	(0.0027)	(0.0026)
F- first stage	34.74	23.53	27.66	89.42
Sargan p-value	0.3167	0.3895	0.1172	0.1109
Dependent variable:Δwhite/blue-collar workers				
ΔShare of labor that uses Internet	0.0012	-0.0038**	-0.0007	0.0021***
	(0.0011)	(0.0015)	(0.0011)	(0.0007)
F- first stage	32.65	26.07	25.72	68.15
Sargan p-value	0.6403	0.3005	0.1782	0.4398
Dependent variable:Δwhite/blue-collar wages				
ΔShare of labor that uses Internet	-0.0239***	-0.0015	-0.0119	-0.0308***
	(0.0065)	(0.0070)	(0.0073)	(0.0044)
F- first stage	30.427	24.40	26.33	85.22
Sargan p-value	0.2314	0.5965	0.5226	0.8058
Observations	1,560	1,560	1,561	1,560

Robust standard errors in parentheses

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

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

Table 23: IV estimates of the effect of the share of labor with Internet on labor outcomes by quartile of income-per-worker growth: Commerce

	1st quartile	2nd quartile	3rd quartile	4th quartile
Dependent variable: Δln(Number of white-collar workers)				
ΔShare of labor that uses Internet	0.0089***	0.0019***	0.0002	-0.0014**
	(0.0020)	(0.0006)	(0.0004)	(0.0007)
F- first stage	69.89	403.459	588.263	424.73
Sargan p-value	0.4155	0.7261	0.5122	0.7041
Dependent variable: Δln(Number of blue-collar workers)				
ΔShare of labor that uses Internet	0.0230***	0.0018***	-0.0017***	-0.0073***
	(0.0023)	(0.0004)	(0.0003)	(0.0006)
F- first stage	75.62	387.54	331.82	406.88
Sargan p-value	0.3642	0.4130	0.3901	0.3294
Dependent variable: Δln(Wage of white-collar workers)				
ΔShare of labor that uses Internet	-0.0142***	-0.0006	0.0008*	0.0093***
	(0.0022)	(0.0006)	(0.0004)	(0.0007)
F- first stage	69.82	405.46	588.26	423.86
Sargan p-value	0.8328	0.5629	0.5028	0.8573
Dependent variable: Δln(Wage of blue-collar workers)				
ΔShare of labor that uses Internet	-0.0196***	-0.0040***	-0.0012***	0.0073***
	(0.0021)	(0.0005)	(0.0003)	(0.0006)
F- first stage	75.54	389.01	568.87	405.73
Sargan p-value	0.1923	0.3044	0.9288	0.7811
Dependent variable:Δwhite/blue-collar workers				
ΔShare of labor that uses Internet	-0.0033***	-0.0000	0.0003**	0.0010***
	(0.0007)	(0.0002)	(0.0001)	(0.0002)
F- first stage	62.44	367.19	554.69	341.20
Sargan p-value	0.9529	0.8944	0.1750	0.1086
Dependent variable:Δwhite/blue-collar wages				
ΔShare of labor that uses Internet	0.0172***	0.0081***	0.0053***	0.0053***
	(0.0038)	(0.0013)	(0.0009)	(0.0014)
F- first stage	73.70	386.34	585.84	299.24
Sargan p-value	0.1689	0.1290	0.3202	0.3571
Observations	2,083	2,084	2,083	2,083

Robust standard errors in parentheses

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

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

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

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). Due to 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, 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 24 shows how the increase in ICT use measured as the change in the share of labor that uses computer is associated with a higher change in the score in terms of administration and production activities. As the results show, a 10 percentage-point increase in ICT use increases the score by around 0.10 for administration activities. Analyzing the activities that are more enhanced within the firm as a result of ICT adoption, in Table 25 we observe that invoicing, the relation with suppliers, sales and accounting are the ones more highly correlated with an increasing 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 shows that the score in terms of processes and products design are increased equally as a result of

a more intensive use of ICT (Table 26).

To 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 27 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).

Table 24: IV regressions of ERP variables on ICT use

	Administration	Production
ΔShare of labor that uses computer	0.0102***	0.0102***
	(0.00312)	(0.00334)
F- first stage	14.150	14.150
Sargan p-value	0.2876	0.5240
N	641	641

Robust standard errors in parentheses.

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

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

Table 25: 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
ΔShare of labor that uses computer	0.00234	0.00511*	0.0119***	0.0186***	0.0191***	0.00629	0.0151***	0.00742**
	(0.00206)	(0.00292)	(0.00389)	(0.00509)	(0.00526)	(0.00430)	(0.00586)	(0.00360)
F- first stage	14.150	14.150	14.150	14.150	14.150	14.150	14.150	14.150
Sargan p-value	0.2070	0.1762	0.1972	0.5515	0.1943	0.3596	0.9469	0.8394
N	641	641	641	641	641	641	641	641

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

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

Table 26: IV regressions of ERP Production variables on ICT use

	Processes	Products
ΔShare of labor that uses computer	0.0109***	0.00939**
	(0.00396)	(0.00384)
F- first stage	14.150	14.150
Sargan p-value	0.8987	0.3312
N	641	641

Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

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

Table 27: IV regressions of Internet use scores on ICT use

	Internet use	Information	Customers and Suppliers	Payments and finance	Marketing	Human Resources
ΔShare of labor that uses internet	0.0243***	0.0106***	0.0481***	0.00580*	0.0135**	0.0451***
	(0.00448)	(0.00263)	(0.00915)	(0.00323)	(0.00616)	(0.00857)
F- first stage	18.178	18.178	18.178	18.178	18.178	18.178
Sargan p-value	0.9991	0.6907	0.8827	0.4302	0.8875	0.6023
Observations	641	641	641	641	641	641

Standard errors in parentheses.

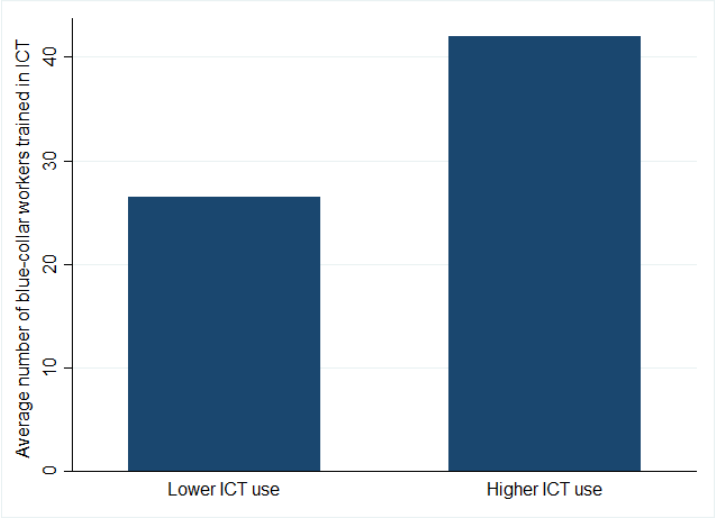
* p<0.10, ** p<0.05, *** p<0.01

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

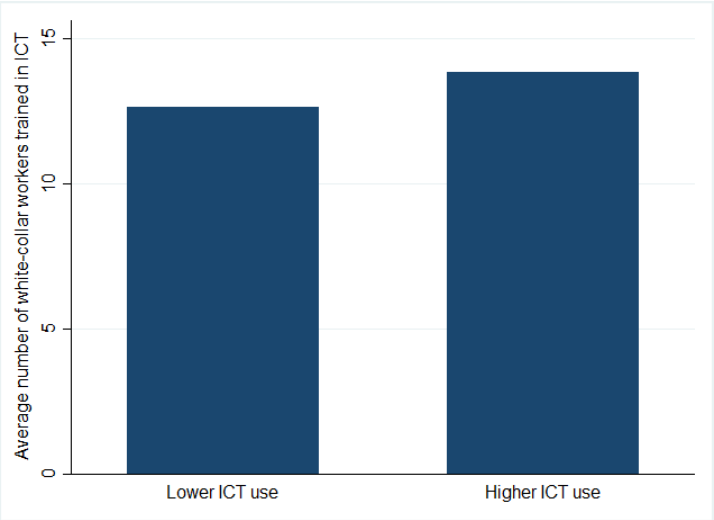
As one of the possible explanations for the increase in wages of blue-collar workers is that they are becoming more sophisticated and thus, some of them instead of being substituted by ICT are becoming complements of these technologies, we analyze a variable regarding the number of workers that are trained in ICT according to their skill-level (white-collar and blue-collar). As Figure 10 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 10: 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 output, growth and productivity, but also that have important effects over the firm organization and labor demand. Therefore, these technologies affect wages of different levels of skills as explained through the literature regarding skill-biased technical change and job polarization. Consequently, the analysis of this process at

the firm level is important for explaining the dynamics of wage inequality at the country level.

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, services and commerce firms from the two last Economic Censuses. Our results for the manufacturing sector 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 a more intensive 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 among 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 on average as a result of ICT adoption. On the other hand, for the commerce sector, an increasing ICT use is associated with a higher wage gap between these two groups.

Our results are important in terms of their policy implications for the case of a developing country such as Mexico. Contrary to the predictions of the SBTC literature, the number of unskilled workers proxied by blue-collar workers and their wages are not decreasing as a result of ICT adoption, but instead this kind of workers are becoming more sophisticated and increasing their use of these technologies therefore improving their wages. In this sense, activities aimed at promoting ICT use can be effective not only to enhance firm-level productivity, but also as a mechanism to reduce wage inequality.

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Appendix A Sample construction

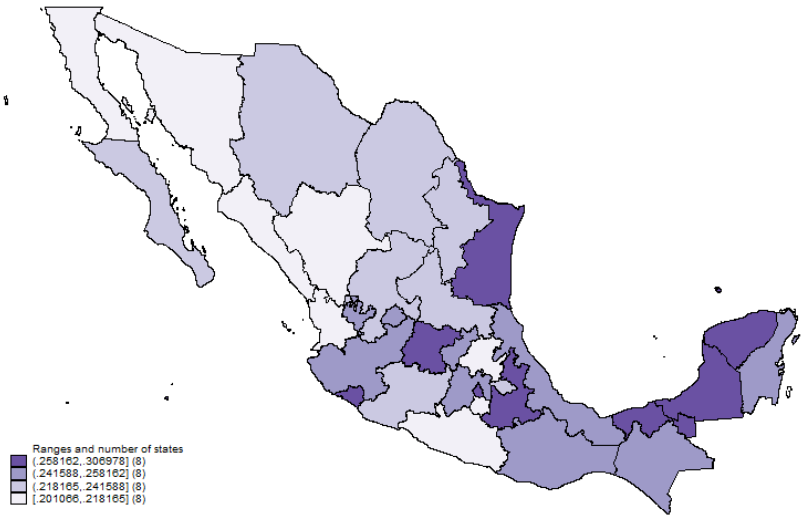
We used the 2009 and 2014 Economic Censuses to construct our database. The 2009 Economic Census includes 3,724,019 observations while the 2014 Economic Census consists of 4,319,608 establishments. From them, using the establishment id, which is the same across all INEGI's projects, we were able to match 2,159,804. The results of this matching indicate that 1,564,214 establishments ceased to exist during this period, while 2,070,941 were created between 2009 and 2013.

From this sample of 2,159,804 establishments that appear in both Censuses, we excluded microenterprises, that is, establishments that have fewer than ten employees. The main reason for excluding establishments of this size is that the module that includes information about the use of computer equipment and Internet use, which are the main explicative variables of this study, was not applied to microenterprises. Therefore, cutting microentrerprises from the 2009 Economic Census leads us to a new sample size of 127,043 establishments and once we drop establishments of this size for the 2014 Census, we end up with 90,422 observations. Furthermore, some small firms did not answer this module either, further reducing our sample to 57,447 observations when we cut these observations for the 2014 Census and to 30,928 when we exclude the ones that do not have responses for these variables in the 2009 Census. As the focus of this study is on wages and labor outcomes, we further restricted our sample by cutting 4,666 establishments that did not register paid workers. Finally, we exclude 250 observations from the mining and oil sectors that have very different characteristics in comparison to the rest of the sectors included in the sample.

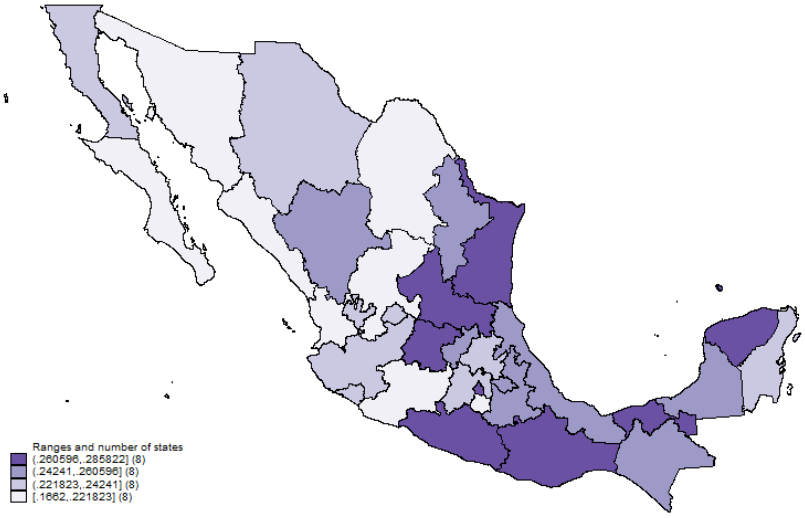
Appendix B Geographic analysis of ICT use and main outcomes: Services and Commerce

Figure B.1: Average Labor ratios by state: Services

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



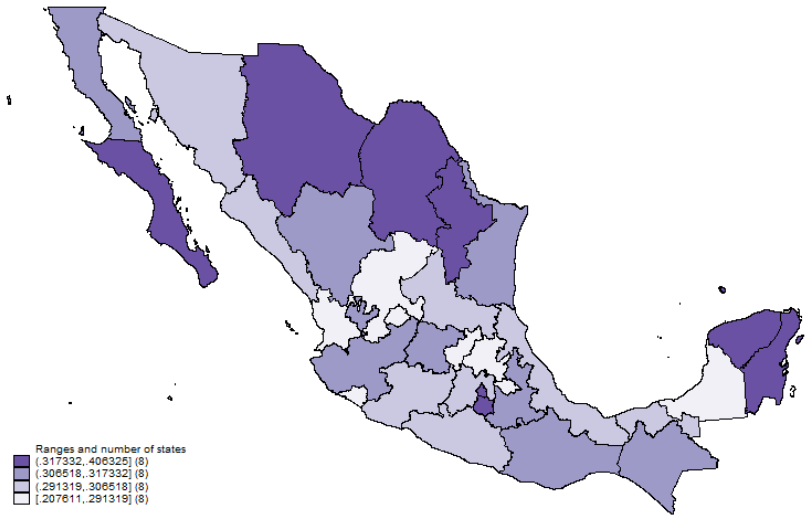
(b) *Number of white/blue-collar workers 2013*



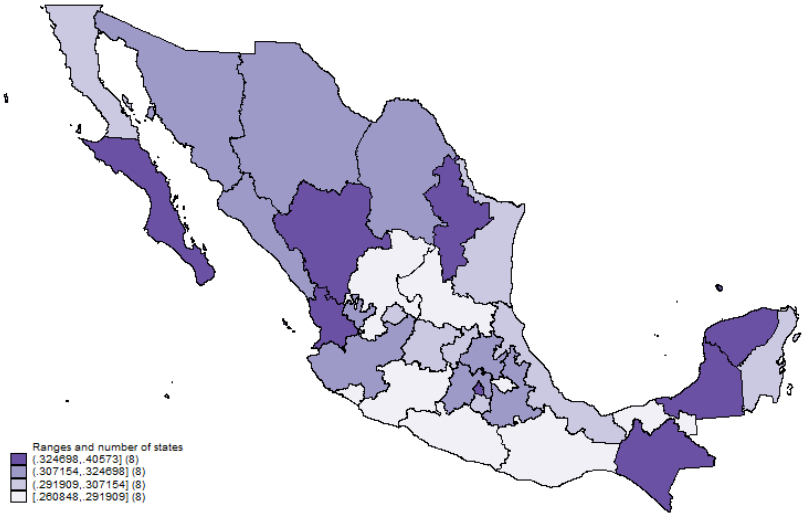
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure B.2: Average Labor ratios by state: Commerce

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



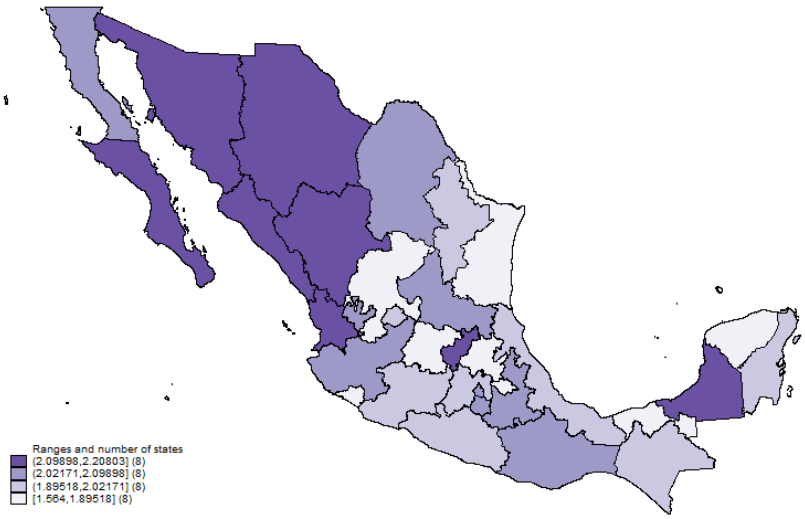
(b) *Number of white/blue-collar workers 2013*



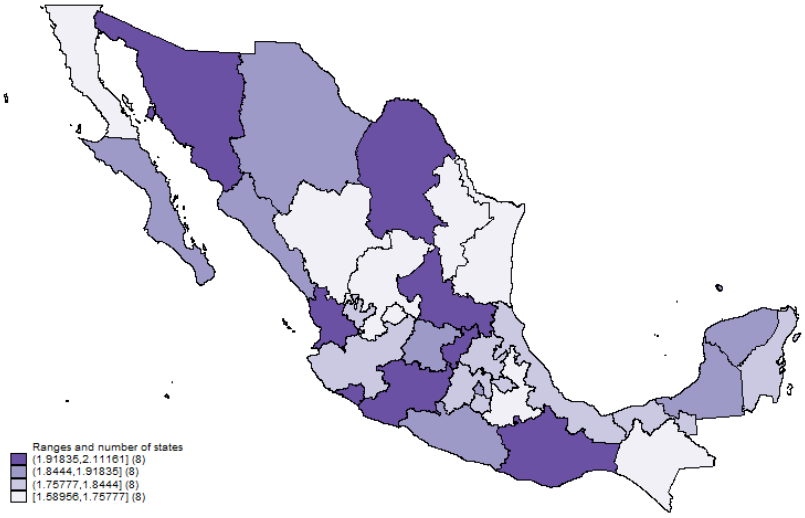
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure B.3: Average Wage gap by state: Services

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



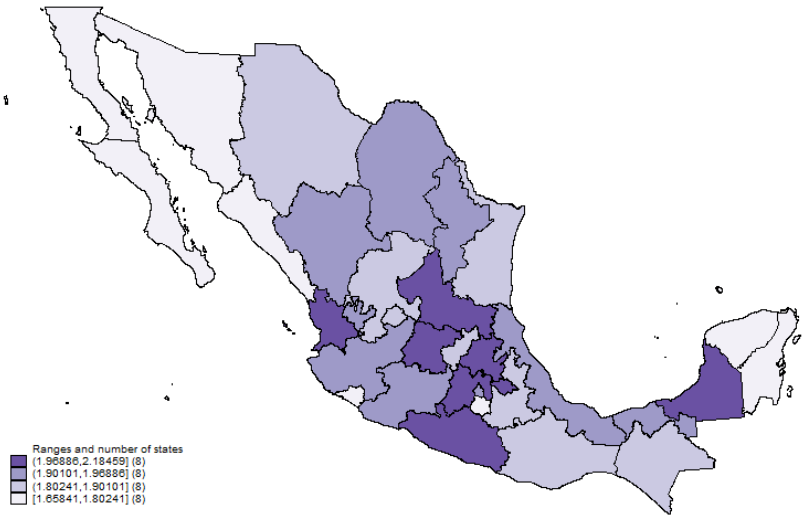
(b) *Wage gap of white/blue-collar workers 2013*



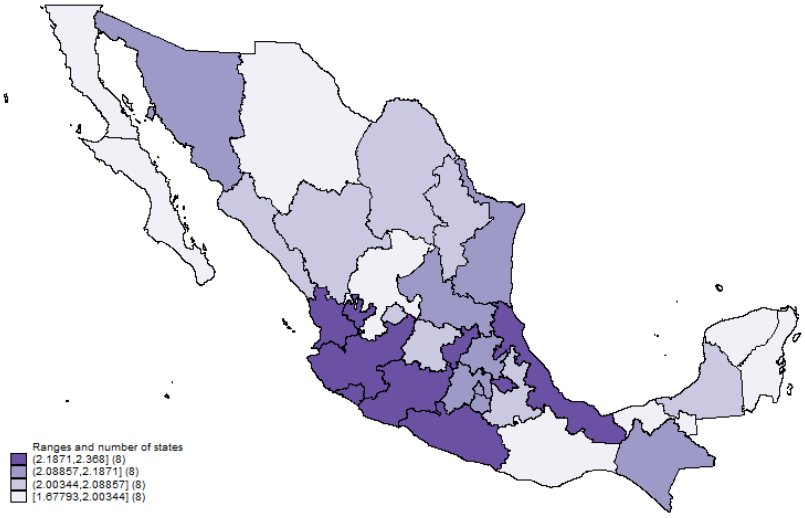
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure B.4: Average Wage gap by state: Commerce

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



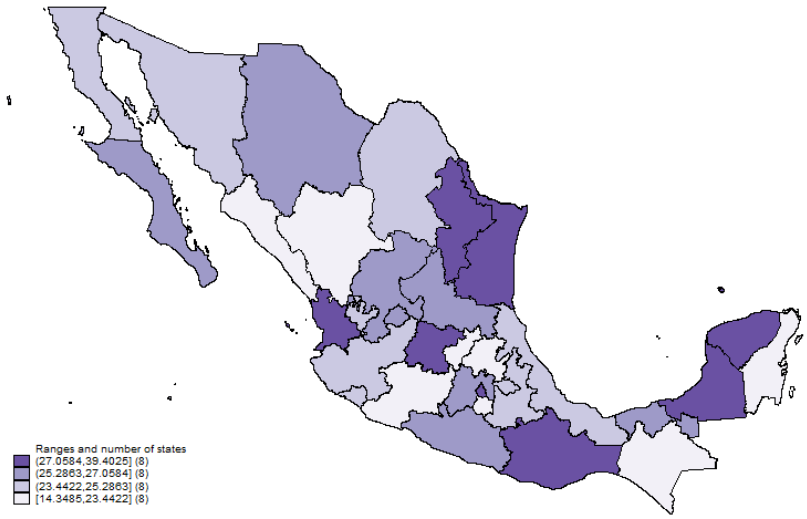
(b) *Wage gap of white/blue-collar workers 2013*



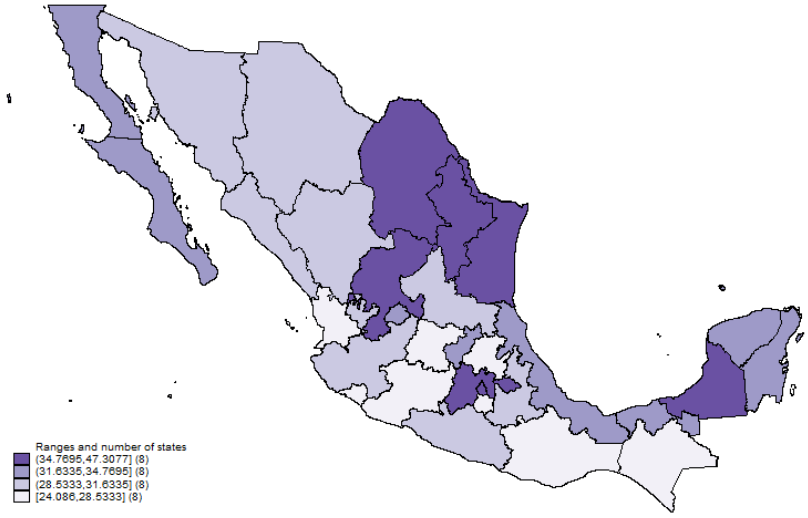
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure B.5: ICT use by state: Services

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



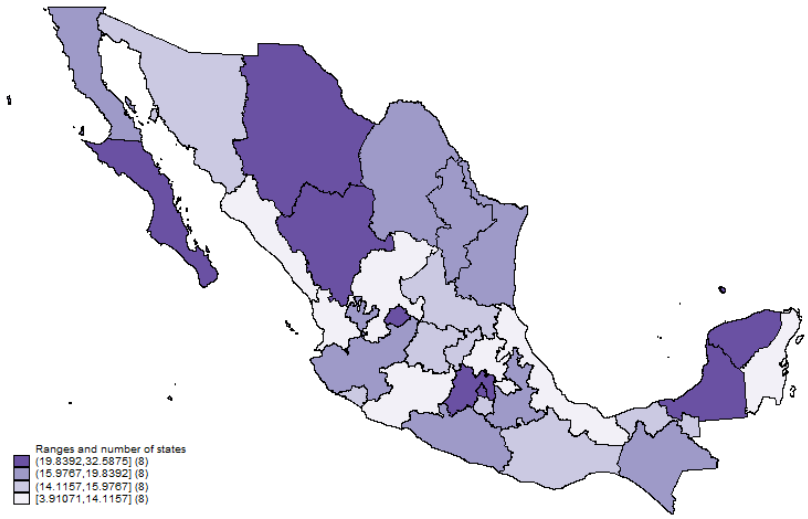
(b) *Share of labor that uses computers 2013*



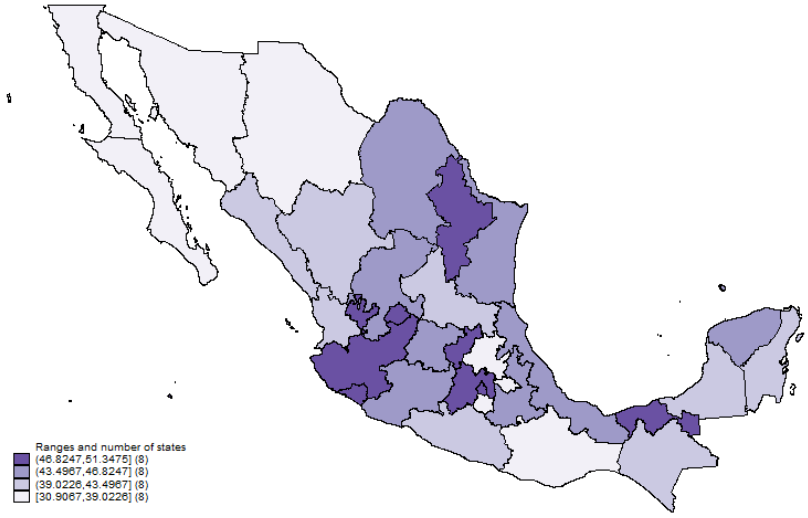
Source: Authors' calculations with data from the 2009 and 2014 Economic Censuses, INEGI.

Figure B.6: ICT use by state: Commerce

(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 Censuses, INEGI.