CESifo WORKING PAPERS

6798
2017

December 2017

The Impact of Digital Technologies on Worker Tasks: Do Labor Policies Matter?

Rita K. Almeida, Carlos H. L. Corseuil, Jennifer P. Poole

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: www.CESifo-group.org/wp

CESifo *Working Paper No. 6798*
Category 14: Economics of Digitization

The Impact of Digital Technologies on Worker Tasks: Do Labor Policies Matter?

Abstract

Between 1999 and 2006, Brazilian cities experienced strong growth in the provision of internet services, driven in part by the privatization of the telecommunications industry. A main concern of policymakers is that digital technology replaces routine, manual tasks, displacing lower-skilled workers. In Brazil, stringent labor market institutions exist to protect workers from such shocks, but by increasing labor costs, labor policy may also constrain firms from adjusting the workforce and fully benefiting from technology adoption. We show that digital technology adoption shifted the demand for skills toward an increased use of non-routine and cognitive tasks. Furthermore, and in contrast with labor policy intentions, we show that *de facto* labor market regulations differentially benefit the most skilled workers, particularly those workers employed in non-routine and cognitive tasks. Our results point to important changes in the future of labor markets in middle-income settings and warn for distortive and unintended consequences of labor market policies.

JEL-Codes: J240, J480, O300, O150.

Keywords: digital technology, skills, labor regulations.

Rita K. Almeida
The World Bank
ralmeida@worldbank.org

Carlos H. L. Corseuil
IPEA
carlos.corseuil@ipea.gov.br

*Jennifer P. Poole**
American University
School of International Service
4400 Massachusetts Avenue, NW
USA - Washington, DC 20016
poole@american.edu

*corresponding author

This version: October 2017
This work has benefitted from funding by the World Bank's Latin America and Caribbean Chief Economist Office, under the regional study "Digital Technology Adoption, Skills, Productivity, and Jobs in Latin America". Carlos Corseuil acknowledges financial support from CNPq. Ivette Contreras, Jon Mallek, Nadine Neumann, and Katcha Poloponsky provided excellent research assistance. We thank Miriam Bruhn, Lourenço Paz, Pascual Restrepo, and Diego Vera-Cossio for helpful discussions, as well as workshop participants at American University, the World Bank, the American Economic Association annual meetings, the International Studies Association annual meetings, IPEA, the Midwest International Economic Development Conference, NBER IT and Digitization Summer Institute, and the Geneva Trade and Development workshop.

1. Introduction

Economists have long recognized the efficiency gains from technological change. However, there is also concern that routine, manual tasks are increasingly being replaced by technology, displacing lower-skilled workers (Autor, Levy, and Murnane 2003). The gains from a more productive and flexible economy, in the long run, may be accompanied, in the short term, with increased unemployment and poverty for some workers. The ultimate impact on workers will be mediated by the flexibility that businesses face to adjust their workforce following shocks. While labor market institutions exist to protect workers from shocks, they may also hamper the firm's incentives to adjust the workforce by raising the costs of labor. In this paper, we estimate the impact that digital technology adoption has on the task content of occupations among Brazilian jobs. We further investigate how the stringency of labor market regulations influences the incentives of firms to adjust the use of different types of skills in response to the technology shock. Our paper, therefore, informs the inherent policy trade-off—between job security for workers, on the one hand, and economy-wide productivity and growth, on the other hand—arguably one of the most prominent public policy debates around the globe.

Between 1999 and 2006, Brazilian cities progressively gained access to internet services. Meanwhile, the enforcement of labor market regulations was also quite heterogeneous across the country. While only 15 percent of the over 5,000 Brazilian cities had local internet service in 1999, access to digital technologies has grown considerably since then. By 2006, over half of all municipalities had a local internet service provider. This paper assesses how the rollout of the provision of internet services changed the demand for different types of skills by businesses. In addition, we assess the extent to which *de facto* labor regulations, captured by the enforcement of labor regulations, differentially impacted the decision of firms to adjust their use of different types of skills.[1]

[1] The *de jure* labor regulations in Brazil, established in the 1988 Federal Constitution, are effective throughout the country. However, as the Ministry of Labor is designated with enforcing compliance with regulations, there is significant heterogeneity both within the country and over time in terms of how binding is the labor law.

Our empirical strategy to estimate the effect of digital technologies on the demand for skills relies on substantial variation across three dimensions: municipalities, industrial categories, and time. We take advantage of the fact that industries vary in their degree of reliance on digital technologies in a pre-determined manner, by interacting our main technology variable—related to the supply of local internet service—with industry-specific information on the demand for information and communications technology. Industries that use information technology intensively and that are located in cities that have early access to internet services are likely early adopters of digital technologies. The fact that the internet rollout varied across municipalities and over time makes it possible to control for municipality-specific and time-specific effects. Therefore, the identification of the effect of technology uses across-municipality differences in internet services provision over time for industries that differentially use information technology. Furthermore, we explore the fact that Brazilian employers are exposed to varying degrees of *de facto* labor regulations, as measured by the number of Ministry of Labor inspections per establishment in the city and broad sector, and analyze how the effect of digital technologies on the demand for skills depends on the enforcement of labor regulations.

Our main findings suggest that technology-intensive industries located in cities with earlier access to the internet reduce their relative reliance on manual and routine tasks, thereby shifting the skill composition of industries and cities toward cognitive and non-routine tasks. Among the set of routine tasks, tech-intensive industries located in cities with earlier access increase their relative use of cognitive skills as compared to manual skills in the aftermath of technology adoption. In addition, the evidence shows that the stringency of the enforcement of labor market regulations at the subnational level matters for the extent of the adjustment. In contrast with labor policy intentions, our results suggest that labor market regulations differentially benefit the use of more non-routine and cognitive tasks.

A large body of research has been devoted to the important topic of the labor market consequences of technological change. Digital technologies are one of the main drivers of the world economy today and their impact on the labor market is a topic of continuous discussion. The debate is supported by the empirical relationship between the expansion of technology over the last decades and the coincident polarization of the labor force, leading to a decrease the share of middle-skilled jobs, while the employment shares of high-skilled and low-skilled jobs increase (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011).

Though this correlation is well-established for developed countries[2], the evidence is still scarce for emerging economies. Messina, et al. (2016) analyze the task content of jobs in Bolivia, Chile, Colombia, El Salvador, and Mexico. In their analysis, only Chile shows possible job polarization. This runs counter to evidence in Almeida, et al. (2017), which finds that the adoption of advanced digital technology by Chilean employers shifts employment away from skilled workers, expanding routine and manual tasks. Maloney and Molina (2016) also offer a descriptive perspective of job polarization in the developing world, examining data from 21 countries in Latin America, Asia, the Middle East, and Africa. Only for the cases of Brazil and Mexico did they find a relative reduction of routine jobs, suggesting potentially polarizing forces. Riva (2016) tests the hypothesis by using the 1991 market liberalization of computers in Brazil as a natural experiment, in order to identify the effects of computerization on occupational composition. The evidence shows that the availability of computers at a lower price displaced labor from routine to non-routine tasks. Hjort and Poulsen (2017) analyze the impact of fast internet arrival on labor market outcomes for African countries. They point to a positive effect on employment, which is not homogeneous across skill levels. Assessing the impacts of digital technology adoption on the relative use of skill in a middle-income country is hence one of the important contributions of this paper. To our knowledge, the only other paper assessing the impact of technology adoption on the skill content of jobs in a developing country context is Almeida, Fernandes, and Viollaz (2017).[3]

[2] See, for example, Autor, Levy, and Murnane (2003), Goos, Manning, and Salomons (2009), Acemoglu and Autor (2011), Goos, Manning, and Salomons (2014), Akerman, et al. (2015), Böckerman, et al. (2016), and Acemoglu and Restrepo (2017) for research on industrialized countries.

[3] However, unlike us, their work focuses on the medium-term impact of the adoption of an advanced software within firms. Unlike the Brazilian data, where there is detailed information on the occupational disaggregation within firms, the Chilean data is less detailed.

There is also a large and growing literature on the implications of regulations on the labor market (e.g., Kugler (1999), Kugler and Kugler (2009), Ahsan and Pages (2009), Petrin and Sivadasan (2013), and several other studies cited in Heckman and Pages (2004)). However, Bertola, et al. (2000) suggest that differences in enforcement are as, or even more, important than differences in regulations for labor market outcomes. Especially in a developing country context where enforcement is not homogeneous, we argue exploiting time-series and within-country variation in regulatory enforcement, captured by labor inspections, offers a better measure of an employer's flexibility in adjusting labor following the adoption of new technology than looking at variations in *de jure* regulations. Therefore, our second main contribution is that we are the first paper allowing digital technology to impact the demand for skills differently depending on the degree of enforcement of labor market regulation. In fact, to our knowledge, we are the first paper to consider the impact of any labor market shock on the demand for skills in different labor market regulatory environments.[4] We investigate the differential impact of digital technologies on skills among otherwise identical industries facing different *de facto* enforcement of the labor law, based on their municipal location.

These contributions are made possible by relying on innovative data sets allowing us to link access to digital technology to labor market policies and outcomes. First, we exploit a matched employer-employee database from the Brazilian Ministry of Labor with detailed information on the occupation of each worker employed in the formal sector, and match it to subnational data on the municipal rollout of internet services over time. To our knowledge, we are the first to explore this unique municipal data set with time-series and within-country variation in access to digital technologies.[5] This administrative data allows us to analyze the impacts of digital technology adoption on labor market outcomes at the city and industry level, across broad sectors and regions of the country. Second, we exploit a concordance between the Brazilian Classification of Occupations (CBO) and the U.S. Department of Labor's

[4] Almeida and Poole (2017) allow for labor market institutions in analyzing the impact of trade reform on employment levels.
[5] Dutz, et al. (2017) rely on a different database from Brazil to consider internet rollout over time and across municipalities in the country.

Occupational Information Network (O*NET) to measure the task content of occupations, or how intensive is the use of “cognitive”, “manual”, “non-routine”, and “routine” tasks within each occupation. With these variables, we calculate each municipality-by-industry’s average task content across its workforce and use it as our main dependent variable. Third, we exploit administrative information on the enforcement of labor market regulations, captured by the municipal incidence of labor inspections (as published by the Brazilian Ministry of Labor).

The rest of this paper is organized as follows. Section 2 offers an overview of the main theoretical predictions relating technology adoption and the subnational enforcement of labor regulations to labor market outcomes. Section 3 presents the main data sets and provides descriptive statistics. Section 4 presents the identification strategy, while section 5 describes the main results for the effects of technology on the use of skills across distinct regulatory environments, with select robustness checks for the validity of our empirical strategy alongside. We offer conclusions and policy implications in the final section.

2. Digital Technology, Labor Policy, and Skills

This section offers a brief overview of the theoretical arguments linking labor market outcomes and technological change. We also present a summary of the theoretical predictions on the labor market implications of regulatory enforcement. Theory offers ambiguous predictions, and thus, these are inherently open empirical research questions.

2.1. Digital technology and labor market outcomes

The implications of technical change, including computers and the internet, on the use of different skill groups is theoretically ambiguous, depending on the degree to which workers are substitutes or complements for technology. Digital technologies may replace more sophisticated, cognitively-oriented, skilled tasks, as computers substitute for skilled workers, suggesting a relative increase in the demand for unskilled workers. Alternatively, to the extent that higher-skilled workers complement the new computer-based tasks associated with digital technologies, and computers perform routine, codifiable tasks, substituting for lower-skilled workers, we may expect a relative increase in the demand for skilled workers performing non-routine, cognitive tasks with enhanced technologies.

While both effects may play a role, we hypothesize that the expansion of digital technologies shifts labor demand away from routine, manual tasks toward more non-routine, cognitive tasks, as skill-biased technology substitutes for routine work, following the work presented in Acemoglu and Autor (2011). The authors propose a two-factor model where high-skilled and low-skilled jobs are imperfect substitutes and technology complements both types of workers. In their framework, "routine-biased technological change," also known as the routinization hypothesis first introduced by Autor, Levy, and Murnane (2003), is a main driver of job polarization.[6] Theory predicts that computers substitute for routine tasks and complement non-routine tasks, thereby reducing the relative demand for routine tasks and raising the relative demand for non-routine tasks, and contributing to job polarization. Therefore, though digital technologies can increase economic output, such technological change may leave some workers worse off (Brynjolfsson and McAfee 2011).

2.2. Enforcement of labor policy and labor market outcomes

Employers weigh the costs and benefits of complying with labor regulation. They decide whether to hire formally, informally, or formally but without fully complying with specific features of the labor code (e.g., avoiding the provision of specific mandated benefits, such as health and safety conditions or maximum working lengths, or avoiding payments to social security). The expected cost of evading the law is a function of the monetary value of the penalties (fines and loss of reputation) and of the probability of being caught. In turn, the probability of being caught depends on the employer's characteristics (such as size and legal

[6] Like in our work, the authors classify tasks into two main groups: routine tasks and non-routine tasks. Routine tasks are rule-based activities that, once codifed, can be executed by a machine. Non-routine tasks either require intuition and problem-solving skills for the more abstract, cognitive, non-routine tasks, or situational adaptability and in-person interactions for the more manual, non-routine tasks.

status) and on the degree of enforcement of regulation in the city where the employer is located.

To our knowledge, there are no theoretical papers assessing the impacts of technology depending on the industry's exposure to labor market regulatory enforcement. Here, we concentrate our theoretical analysis on the impact of enforcement on labor market outcomes and offer predictions for how the adjustment to a technology shock may be altered by enforcement. Specifically, we argue that the impact of enforcement on skill composition will depend on the relative cost to adjust labor across skill groups. Stricter enforcement raises the cost of formal workers, in the sense that the higher the compliance with labor legislation, the higher the labor cost for firms. Almeida and Carneiro (2009), Almeida and Carneiro (2012), and Almeida and Poole (2017) document evidence compatible with this view. These higher labor costs tend to increase the cost of adjustment for labor use. Hence, otherwise identical companies facing stricter enforcement of the labor law have increased difficulties in adjusting labor to shocks.

It is plausible that at least some of the labor adjustment cost is proportional to the cost of labor, and would thus be higher for skilled (more experienced) workers than for unskilled workers. For example, in Brazil, dismissal costs are proportional to wages. Hence, we conjecture that, following a technological shock, stringent enforcement of labor market regulations at the subnational level restrict needed labor adjustments relatively more for skilled workers than for unskilled workers in the formal sector. This is consistent with evidence presented in Montenegro and Pages (2004). The authors provide support for the idea that labor market regulations reduce employment rates of the unskilled at the benefit of the skilled workforce. Therefore, in response to the same technology shock, industries located in strongly-enforced municipalities should increase the relative demand for skills by more than industries located in weakly-enforced municipalities.

3. Data and the Brazilian Labor Market

The experience of Brazil captures well the typical middle-income economy where the rollout of digital technology was gradual. In order to assess the effects of this rollout on the Brazilian labor market, we rely on administrative data to measure the skill content of occupations for all formal-sector workers in the economy. We characterize the tasks required in each worker's occupation, based on data describing the abilities required and activities performed in similar occupations in the United States. We then aggregate this information on skill composition to the industry-municipality-year level. We merge these outcomes of interest to city-by-time information on the municipal rollout of internet services, to industry-specific information on the use of information and communications technology, and city-by-sector-by-year information on the enforcement of labor market regulations.

3.1. Task content of jobs in the Brazilian formal labor market

We exploit administrative data, collected by the Brazilian Labor Ministry and reported in the *Relação Anual de Informações Sociais* (RAIS), which captures the yearly formal workforce across all registered establishments in the country. We use this data for the years 1999 through 2006, when the provision of internet services had a rapid rollout across the country. The main benefit of the RAIS database is that it offers information on workers' skill levels beyond many similar datasets that rely exclusively on education variables. We take advantage of a highly-detailed (5-digit) codification system for occupations to define skill levels using a task-based approach. In addition, RAIS also includes the industry and municipality of each establishment.[7] We restrict observations as follows. First, we exclude from the analysis the public and the agricultural sectors, as the Ministry of Labor has recognized issues of data quality there. Moreover, labor adjustment in the public sector is not likely to respond to the same forces as labor adjustment in the private sector. Second, as is customary in the literature, we drop all establishments that have fewer than five employees.

[7] The industrial classification available in RAIS is the 4-digit National Classification of Economic Activities (CNAE).

At the beginning of our sample, the main employer-employee dataset includes over 16 million workers, employed in 2,312 different occupations in approximately 295,000 establishments, producing in 574 CNAE industries, and located in 3,479 municipalities across Brazil. By the end of our sample period, Brazil's formal labor force had grown significantly to over 22 million workers, employed in 2,350 occupations across around 351,000 establishments, producing in 528 industries, and located in 3,608 municipalities.

We merge this data with information on the task content of occupations measured by the U.S. Standard Occupational Classification (SOC) in the year 2000.[8] The U.S. Department of Labor surveys workers in all occupations about the abilities required and activities performed in the occupation. O*NET offers "importance scores" ranging between 1 and 5 for 52 different "abilities" and 41 different "activities" associated with an occupation. A score of 1 means that a given attribute is "Not Important" to the occupation, while a score of 5 means that the attribute is "Extremely Important" to the occupation.[9] Our assumption in using data from the United States is that the same attribute (activities or abilities) are required in similar occupations in Brazil. Even if the levels of such attributes may be different across the two countries, we argue that the ranking of the importance of such attributes in similar occupations will not drastically differ. For this reason, we rely on O*NET's importance scores of different abilities and activities in U.S. occupations to characterize abilities and activities in Brazilian occupations.

We standardize the scores into a numerical index between 0 and 1 to better interpret O*NET's ordinal importance score ranking across occupations. Denote the importance score

---

[8] We rely on publicly-available concordances from the National Crosswalk Service Center (http://xwalkcenter.org/) and Muendler, Poole, Ramey, and Wajnberg (2004) to convert occupational characteristics from the 2000 SOC to the 1988 International Standard Classification of Occupations (ISCO) to the CBO found in RAIS.

[9] For instance, chief executives score 5 for abilities related to "oral comprehension" and "oral expression", but score 1 for abilities related to "dynamic and explosive strength". Meanwhile, jewelers score high (4.8) for "finger dexterity" and low (1.8) for "written expression". In terms of activities, chief executives score high for activities such as "analyzing data or information" and "making decisions and solving problems" and score low for activities like "controlling machines and processes" and "operating vehicles or equipment", while jewelers score high for activities related to "handling and moving objects" and "judging qualities of things…" and low for activities such as "assisting and caring for others" and "interacting with computers".

for attribute a in a CBO occupation c by $S_{c,a}$. Our normalized scores scale each raw score by the maximum value for that score across the full set of occupations C, as follows:

$$S'_{c,a} = \frac{S_{c,a}}{\operatorname{argmax}\{S_{1,a}, \ldots, S_{C,a}\}}.$$

Our interest is in broader skill groupings than those described in the raw O*NET database. Hence, we aggregate across abilities and activities within a "bundle" for each occupation. We consider two main *ability* bundles: "manual" and "cognitive". Manual abilities are further decomposed into "precision" versus "other" (such as strength-based) tasks. Cognitive abilities are further decomposed into "analytical" versus "communication" tasks. Table 3.1 displays our classification of the 52 O*NET *abilities* into these four distinct bundles. We consider the following *activity* bundles: "routine" versus "non-routine". Routine activities are further disaggregated into "manual" activities and "cognitive" activities. Non-routine activities are also further disaggregated into "manual" and "cognitive" activities. Table 3.2 displays our classification of the 41 O*NET *activities* into these four distinct categories.

In contrast to some papers in the literature relying on O*NET data, we classify and make use of all O*NET abilities and activities, rather than hand-picking a select one or few. We believe this strengthens the value of our results. The results suggest a high-quality match. Appendix Table 1 reports the five Brazilian occupations with the strongest requirements for each broad bundle and the five Brazilian occupations with the weakest requirements for each broad bundle. Chemical engineers are among the most cognitively-oriented occupations, while pyrotechnic detonators are among the most manual-intensive occupations. Trash collectors are among the least cognitive-intensive and historians are among the least manually-oriented occupations. Car washers are among the most routine occupations, while musicians are among the least routine occupations in Brazil. By contrast, nurses are highly non-routine task intensive and knitters and weavers are among the least non-routine task intensive occupations in Brazil.

The final step in calculating our main dependent variables aggregates over all workers (and their respective occupations) in an industry-municipality in a given year. Since the occupation information from O*NET is specific to the year 2000, the time variation in these dependent variables arises only because employers shift the workforce composition over time. Because our interest is in the relative shift of tasks across skill groups, we consider as our main dependent variables the cognitive-to-manual relative task intensity and the non-routine-to-routine relative task intensity in each industry-municipality and year. In column (1) of Table 3.3, we report average values, across all the industry-municipality cells, for these two variables (Panel A and B, respectively). In both cases, the relative value is always less than one, signaling Brazil's comparative advantage in lower-skilled tasks due to an abundance of lower-skilled labor. Over our time horizon, the relative importance of skilled (cognitive and non-routine) tasks in the workforce has marginally increased.

3.2. Digital technology

Rollout of internet services The Internet in Brazil was launched in 1988 but was only made available to the general public in 1995. Since its beginnings, the Brazilian Internet depended strongly on efforts led by the Ministry of Communications and state-owned communications companies (Embratel and Telebras). However, in 1998, with the privatization of Telebras, and the blooming of private companies, such as Telefónica, Telemar, and Brasil Telecom, the dependency on the federal government was reduced. With the surge of competition, there were significant improvements in cost, quality, and a rapid increase in the availability of the internet to all Brazilians. According to the International Telecommunications Union, in 2010, Brazil ranked 9th in the world with 13,266,310 fixed broadband subscriptions, 6.8 subscriptions per each 100 residents.

Beginning in 1999, the Brazilian Census Bureau (IBGE) has conducted an annual survey of all Brazilian municipalities, the *Pesquisa de Informações Básicas Municipais* (MUNIC), on the structure and functions of municipal institutions. In the years 1999, 2001, 2005, and 2006, the survey specifically asks questions about the existence of various cultural activities including whether the city has a company that provides internet services. Table 3.4 presents basic descriptive statistics for this variable. While only 15 percent of the over 5,000 Brazilian cities had local internet service in 1999, access to digital technologies has grown considerably since then. By 2006, over half of all municipalities had a local internet service provider. Though not all cities have access to the internet, areas of the country with internet services are larger population centers. In 1999, internet access had spread to roughly 60 percent of the Brazilian population and by 2006, almost 90 percent of the population had a local internet service provider.

The map in Figure 3.1 illustrates the spread of the internet across the country over time. The darker areas of the map, also more urban and richer areas, obtained internet services earlier than the lighter areas on the map. The municipalities in white are those cities that remain without internet service in 2006. Most of these cities report lower per capita gross domestic product (GDP), larger rural areas, and weaker infrastructure. A casual observation suggests no substantial clustering of the rollout, but this can be difficult to view given the geographic scope of the country. In Figure 3.2, we illustrate the rollout of the internet in the most populous and developed state, São Paulo. Even in this state, we notice considerable over time and across municipality variation. This is exactly the variation that we rely on in our paper.

Returning to Table 3.3, in columns (2) and (3), we report the average cognitive-to-manual task ratio (Panel A) and the non-routine-to-routine relative task intensity (Panel B), conditioning on whether the city has internet service provision by 2006. Perhaps unsurprisingly, industries located in cities with internet access consistently employ higher shares of workers in skilled tasks.

Industry-specific information technology intensity Following Oldenski (2014), we rely on data from the U.S. Census Bureau's *Current Population Survey* (CPS), to compute our main measure of the industry's technological intensity. In an October 2003 supplement, the survey asked respondents whether they use a computer at their current job. Aggregating across all workers within their reported industrial categories, we calculate the share of workers in U.S.

industries who report using a computer at work. We then rely on publicly-available concordances (Muendler 2002) to measure the intensity of technology use across over 100 Brazilian industries, based on the U.S. data.

The information from the United States in 2003 is used here as a proxy for the demand for technology in Brazil across industries; that is, how intense would be the use of technology across industries in Brazil if such technology was as widespread as in the United States. As with the O*NET data, our use of U.S. data assumes that while the levels may be different for a given industry across the two countries, the ranking of industries by their information technology intensity is not different, once the two countries experience the same supply level of internet service. The data report that the "electronic computer manufacturing" and "peripherals manufacturing for data processing equipment" rely most heavily on technology, with over 85 percent of workers reporting using a computer at work. "Farm machinery and equipment manufacturing," "paper manufacturing," and "paperboard containers and coated paperboard manufacturing" measure the least technology intensive industries, with less than 30 percent of workers reporting use of a computer at work.

Returning again to Table 3.3, in columns (4) and (5), we report the average relative task compositions, conditioning on whether the industry is technologically-intensive (as defined by the median value). Perhaps unsurprisingly, tech-intensive industries consistently employ higher shares of workers in cognitive and non-routine tasks. The difference is increasing over time—tech-intensive industries employ relatively greater shares of skilled tasks over time as compared to non-tech-intensive industries.

Our main empirical strategy exploits both the demand for technology as well as the supply of technology to identify the digital technology shock. Columns (6) and (7) of Table 3.3 most closely parallel this empirical strategy using the interaction between internet access and technology use. The average cognitive-to-manual task ratio increases by 3 percentage points between 1999 and 2006 for tech-intensive industries located in cities with internet access. Meanwhile, the same average task ratio decreases by 3 percentage points in non-tech-intensive industries located in cities without internet access, an overall difference of 6 percentage points. Similarly, for the non-routine-to-routine task ratio in Panel B, we see a strong relative shift toward non-routine tasks, measuring around 6 percentage points, particularly for those tech-intensive employers located in municipalities with internet service provision.

3.3. Enforcement of labor regulations

The *de jure* labor regulations in Brazil are effective throughout the country and are rather detailed and stringent. For example, a book that consolidates all Brazilian labor regulation has more than a thousand pages. To employ a formal worker with full compliance with all this regulation can be very costly.[10] According to the World Bank's Doing Business Project, in 2013, Brazil was the country with the highest labor costs (defined as labor tax and contributions relative to commercial profits) in a sample of 10 Latin American countries. Moreover, terminating a formal employment relationship can also be very costly to Brazilian firms. The penalty on the plant for dismissing the worker without cause is around 40% of the total contributions to the severance fund, *Fundo de Garantia do Tempo de Serviço* (FGTS). Brazilian employers who wish to terminate worker contracts must also give advanced notice to workers, and during this interim period, workers are granted up to two hours per day (25% of a regular working day) to search for a new job.

Since the Ministry of Labor is designated with enforcing compliance with labor regulations, there is significant heterogeneity both within the country and over time in terms of how binding is the law.[11] An inspection can be triggered either by a random audit, or by a report (often anonymous) of non-compliance with the law. Workers, unions, the public prosecutor's office, or even the police can make reports. Most of the inspections and subsequent fines for infractions in Brazil are to ensure compliance with workers' formal registration in the

[10] For example, changes to the federal labor laws in 1988 increased the overtime wage premium from 20% to 50% of the regular wage. Additionally, it increased one month's vacation time pay from 1 to 4/3 of a monthly wage.
[11] A comprehensive explanation of the enforcement of the labor regulation system and its importance in Brazil is given in Cardoso and Lage (2007).

Ministry of Labor, contributions to the severance pay fund (FGTS), minimum wages, and maximum working lengths.

We explore administrative city-by-sector-level data on the enforcement of labor regulations, collected by the Brazilian Ministry of Labor. Data for the number of inspector visits are available by city and broad sectoral classification for the years 1998, 2000, 2004, and 2006. For our analysis, we match the enforcement data to the RAIS data by the employer's municipal location and broad industrial classification. This information identifies industries facing varying degrees of regulatory enforcement. Moreover, given the timing of the MUNIC data on internet service provision, our main measure of enforcement used in the analysis that follows is lagged by one year.

We proxy the degree of regulatory enforcement with the intensity of labor inspections at the city-sector level. In particular, our main measure of enforcement, designed to capture the probability of a visit by labor inspectors to employers within a city-sector, is the logarithm of the number of labor inspections at the city-sector level (plus one) per establishment in the city and broad sector (in a pre-shock time period, 1995) based on RAIS. This scaled measure of inspections helps to control for important size differences across cities (i.e., that São Paulo has many inspections, but also many establishments to inspect). In addition, scaling by a pre-reform, time-invariant measure of city-sector size ensures that changes in our main enforcement measure are due to changes in inspections and not changes in the number of formal establishments in the city-sector. Moreover, the impact of such a measure will reflect the direct effect of inspections, as well as the perceived threat of inspections (even in the absence of establishment-specific inspections) based on inspections at neighboring companies.

Table 3.5 presents descriptive statistics on the enforcement of labor regulations nationwide. Over time, as Brazilian regulators attempt to reach a larger share of the labor force, the number of cities with at least one inspection increased—from 55 percent in 1998 to 67 percent in 2006. As inspectors reach more and more cities, the average number of inspections per city-sector also changes significantly—from 69 inspections per city-sector in 1996 to 73 inspections per city-sector in 2006. Our main measure is designed to capture the probability of inspection. In column (3), we scale the number of inspections by the size of the city-sector in 1995 (per 100 registered establishments in the city-sector). The probability of being inspected roughly doubled—from 12 inspections per 100 registered establishments to 23 inspections per 100 registered establishments—between 1998 and 2006.

Our identification strategy relies on the across-city and over-time variation in labor market regulatory enforcement. The standard deviation reported in column (4) of Table 3.5 shows significant heterogeneity across city-sectors within each year. In Figure 3.3, we note the substantial within-country variation in the intensity of enforcement across cities in Brazil. The top panel illustrates the number of inspections per Brazilian city in 1998, with darker shades portraying higher numbers. The bottom panel depicts the same statistic for the year 2006. We remark on the variation across municipalities and over time. First, we observe the darkest areas of the map in the high-income Southern and Southeastern regions of the country. We also notice a darkening of the map over time as enforcement spreads to further parts of the country. Figure 3.4 offers a clearer picture of the across city and over time variation in regulatory enforcement by focusing in on a single state, São Paulo.

4. Identification Strategy

Our empirical strategy to estimate the effect of digital technologies on the demand for skills relies on substantial variation across three dimensions: municipalities, industrial categories, and time. Furthermore, we explore the fact that Brazilian employers are exposed to varying degrees of *de facto* labor regulations, as measured by the number of Ministry of Labor inspections per establishment in the city and broad sector, and analyze how the effect of digital technologies on the demand for skills depends on the enforcement of labor regulations.

4.1. Digital technology shock

We begin with a triple differences-in-differences approach—across municipalities, across industries, and over time—to estimate the effect of access to digital technology on the use of different types of skills. We consider Brazil's internet rollout across cities and over time as the main technological advancement and argue that a similar technological change affects industries differentially based on their reliance on information and communications technology. The effect of digital technology adoption is identified using across-municipality differences in internet services provision over time for industries that differentially use information technology. The main estimating equation is as follows:

$$y_{mkt} = \beta_1(PRO_{mt} * USE_k) + \beta_2 PRO_{mt} + \varphi_{mk} + \delta_{Kst} + \varepsilon_{mkt} \tag{1}$$

where m indexes the municipal location, k indexes the (4-digit) industry, t indexes time, K denotes Brazil's 16 broad sectors, and s denotes the 27 states of the country. We relate the industry-city task ratios (y_{mkt}) to the city-by-time-varying supply-side technological change, the provision of local internet services in a city and year (denoted as PRO_{mt}). β_1, our main coefficient of interest, reports the effects of the supply-side provision of internet services interacted with a time-invariant measure of the industry's technological-intensity (USE_k), or the demand for digital technologies. We argue that the arrival of new internet services impacts industries differently depending on whether they require information and communications technology services. This interaction serves as our main technology shock.

Equation (1) includes interactive city-industry fixed effects (φ_{mk}) to capture time-invariant factors, such as the industry's unobserved underlying productivity or technology, or the city's unobserved level of development, which may influence both the workforce composition, as well as the likelihood of adopting digital technologies. Because of this, the coefficient on a separately-included industry-specific tech-intensity variable (USE_k) is unidentified, and this control variable is absorbed into the fixed effects. We also include state-sector-specific year dummies (δ_{Kst}) to control for the impact of other policy reforms during the period. The fact that the internet rollout varied across municipalities and over time, and technology-intensity varies across industries makes it possible to control for municipality-specific, industry-specific, and time-specific effects in this manner to identify the technology shock. Together, these will be our base set of controls.

We argue tech-intensive industries located in cities with early provision of the internet are more likely to adopt digital technologies. Therefore, when interpreting our results, we focus on the impact of digital technologies in tech-intensive industries ($\beta_1 + \beta_2$). Following Acemoglu and Autor (2011), as well as much of the evidence from the developed world, we hypothesize that $\beta_1 + \beta_2 > 0$, as employers use technology to replace routine, manual tasks shifting the composition of the workforce toward non-routine and cognitive tasks.

To test the robustness of our findings, we estimate the specification in equation (1), including two additional sets of controls. First, as discussed in Section 3.2, richer and larger areas of the country likely gained access to the internet before other cities. Broad cross-sectional differences in development are already captured in our city fixed effects. However, in our intermediate set of controls, we also include time-varying controls for the city's development, which may be considered to be omitted variables correlated with the technology shock. These include city-level controls for GDP, population, and access to credit, as well as indicators of the gender, age, and educational composition of the city. We also add measures of the city-industry's exposure to global markets, defined as the number of exporting (and importing) establishments in the total number of establishments in the city and industry. These last variables, in particular, allow us to rule out the role of outsourcing in driving the changes in the demand for tasks. These additional variables, together with the base set of controls, define our intermediate set of controls. In a second robustness test, we add controls for the city-specific rollout of other technological developments, such as local television and FM radio providers (from MUNIC survey). The addition of these latter variables defines our complete set of controls.[12]

[12] In section 5, we offer two additional robustness checks for the validity of our main identification strategy. We first test for pre-internet trends in task composition across municipalities and industries. Next, we re-estimate our main equation, restricting the sample to only those municipalities with internet services by 2006.

4.2. Effects of regulatory enforcement

As discussed above, the degree to which employers adjust skills in response to a digital technology shock depends on the stringency of the labor market regulatory enforcement they face. We hypothesize that two identical employers may respond differently to such technology shocks depending on their exposure to labor market inspections. We estimate a second empirical specification including city-by-broad sector exposure to Ministry of Labor inspections as follows:

$$y_{mkt} = \gamma_1(ENF_{mKt-1} * PRO_{mt} * USE_k) + \gamma_2(ENF_{mKt-1} * PRO_{mt}) + \gamma_3(ENF_{mKt-1} * USE_k) + \gamma_4 ENF_{mKt-1} + \beta_1(PRO_{mt} * USE_k) + \beta_2 PRO_{mt} + \varphi_{mk} + \delta_{Kst} + \varepsilon_{kmt} \quad (2)$$

where all notation is as previously described. ENF_{mKt-1} represents the one-year lagged value of time-varying, municipality-by-broad sector-level enforcement of labor regulations, as captured by Ministry of Labor inspections.

One concern could relate to the exogeneity of the variation in labor regulations across cities. For example, the enforcement of regulations may be stricter in cities where violations of the labor laws are more frequent or in cities where institutions are more developed. While it is true that violations of labor laws and better institutions are likely also correlated with labor market outcomes, we note that these are statements about the non-random cross-sectional variation in enforcement. The specification in equation (2) includes city-industry fixed effects which helps to minimize any concerns regarding the endogeneity in the level of enforcement, as the main identification is based on changes in the enforcement of labor market regulations, as in Almeida and Poole (2017).

However, one could still question the exogeneity of changes in enforcement at the city-sector level. We note that our empirical methodology has three features to deal with this potential problem. First, we control for another layer of fixed effects that captures specificities on time-state-broad sector cell. Therefore, the relevant variation on labor inspection and potential confounders should happen across municipalities within states. Second, we use lagged values for labor inspection. Finally, we do not rely on the effect associated with the labor inspection variable alone. We rely on differential effects of quasi-exogenous technology shocks for industries located in diverse policy environments—a triple-interaction effect—following a recent trend in the program evaluation literature.

To summarize, our proposed specification minimizes concerns about the endogeneity of enforcement by focusing on within-city-industry changes in enforcement, by focusing our interpretation on the triple-interaction term, and by considering lagged values of the main enforcement measure. Like in equation (1), we are interested in the impact of digital technologies in tech-intensive industries (because tech-intensive industries located in areas with internet services provision are the likely adopters of digital technologies). In equation (2), we are also interested in how tech-intensive industries located in strictly-enforced labor market regulatory environments may respond to technology shocks differently than otherwise identical tech-intensive industries located in weakly-enforced labor market regulatory environments.

To interpret the results from equation (2), we derive the following effects. First, the impact of digital technologies in tech-intensive industries located in strictly-enforced cities (at the 90th percentile of inspections) is calculated as follows:

$$
\begin{gathered}
E[y_{mkt}|PRO_{mt} = 1, ENF_{mKt-1} = s, USE_k = 1) \\
-E[y_{mkt}|PRO_{mt} = 0, ENF_{mKt-1} = s, USE_k = 1) \\
= \gamma_1 s + \gamma_2 s + \beta_1 + \beta_2
\end{gathered}
$$

where s denotes the 90th percentile of inspections in the data. Similarly, we calculate the impact of digital technologies in tech-intensive industries located in weakly-enforced cities (at the 10th percentile of inspections) as:

$$E[y_{mkt}|PRO_{mt} = 1, ENF_{mKt-1} = w, USE_k = 1)$$
$$-E[y_{mkt}|PRO_{mt} = 0, ENF_{mKt-1} = w, USE_k = 1)$$
$$= \gamma_1 w + \gamma_2 w + \beta_1 + \beta_2$$

where w denotes the 10th percentile of inspections in the data. Finally, we calculate the difference in the impact of digital technologies in tech-intensive industries located in strict versus weak enforcement areas as follows:

$$(\gamma_1 s + \gamma_2 s + \beta_1 + \beta_2) - (\gamma_1 w + \gamma_2 w + \beta_1 + \beta_2) = \gamma_1(s - w) + \gamma_2(s - w).$$

We concentrate our interpretation of the differential impact of quasi-exogenous technology shocks on labor market outcomes in different regulatory environments on this difference $(\gamma_1(s - w) + \gamma_2(s - w))$. If labor policies are designed to protect the most vulnerable (least skilled and experienced) workers, we expect that $\gamma_1(s - w) + \gamma_2(s - w) < 0$ as tech-intensive industries located in strictly-enforced municipalities respond to technology shocks by differentially shifting the composition of the labor force toward unskilled (routine and manual) workers. On the other hand, if labor market regulations reduce employment opportunities for the unskilled at the benefit of the skilled (in part due to the higher labor adjustment costs for skilled workers), we predict that $\gamma_1(s - w) + \gamma_2(s - w) > 0$, as tech-intensive industries shift the composition of the workforce toward non-routine, cognitive tasks by more in strict labor market environments.

5. Main Results

This section details our main findings relating digital technology adoption, labor policy enforcement, and the demand for skills.

5.1. Impact of digital technology on skills

Table 5.1 reports results for the estimation of equation (1) by ordinary least squares, with standard errors clustered at the interactive city-industry level.[13] In Panel A, the dependent variable is the logarithm of cognitive-to-manual tasks in the city and industry. In Panel B, the dependent variable is the logarithm of the non-routine-to-routine tasks in the city and industry. Our main parameter of interest is the overall impact of the internet on tech-intensive industries (those industries poised to adopt the new technology), that is, the sum of the coefficients $(\beta_1 + \beta_2)$. This coefficient sum is reported at the bottom of the table, highlighted in bold, along with the corresponding F-statistic for the null hypothesis that the sum is equal to zero.

Columns (1) and (4) report the results for the estimation of equation (1) with city-industry fixed effects and sector-state-year dummies. As we discuss earlier, the theoretical literature suggests that unskilled workers may fare worse with the introduction of new technologies, as they face more severe employment declines, because technology is complementary to high-skilled workers and substitutes for low-skilled workers. Our results confirm this routinization hypothesis for Brazil. The employment reduction in response to technical change of skilled workers is much less than the employment reduction of unskilled workers (see Appendix Table 2 for dependent variables in levels), shifting the composition of the workforce toward cognitive and non-routine tasks. This is evidenced by the statistically-significant and positive coefficient on the impact of technology in tech-intensive industries at the bottom of the first columns of each panel.

In columns (2) and (5), in addition to the basic set of controls reported in equation (1), we also include city and industry time-varying controls potentially correlated with the technology shock—GDP, population, access to credit, the gender, age, and educational composition of the city, and exposure to foreign markets. In unreported results, available by request, we find that larger cities, in terms of population, report higher skill content of jobs (cognitive and non-routine tasks). In addition, consistent with a literature on brain versus

[13] We follow Bertrand, et al. (2004) and always use the same clustering level as the one used to define the fixed effects.

brawn, cities with higher shares of male workers report lower relative cognitive and relative non-routine tasks. Also, unsurprisingly, cities with higher shares of workers with a secondary school education also report higher non-routine-to-routine task ratios. Finally, consistent with the idea that exporting firms are skill intensive, our results report that city-industries with high shares of exporting establishments also report higher relative cognitive and non-routine tasks. Accounting for these controls, the estimates show that our main results remain unchanged. The magnitudes and significance of the coefficients are almost identical to the first columns—the adoption of digital technology shifts local labor market composition toward skilled workers.

In column (3) and (6), we also include additional controls for the city-specific rollout of other types of technological development, as captured by the rollout of local television and FM radio providers. In this estimation, we include these additional city-specific technology rollout controls, as well as their interactions with the industry's technological intensity in parallel to our main internet digital technology shock. This exercise serves as a check that the internet rollout technology shock is not simply capturing some other broad city-specific technological rollout. Once again, the main results are of the expected sign and similar magnitude.

5.2. Digital technologies, labor policy enforcement, and skills

Table 5.2 reports coefficients from the estimation of equation (2) by ordinary least squares with standard errors clustered at the city-industry level. We report all coefficients of interest in the top half of the table. We also report: a) the impact of the internet in tech-intensive industries in strictly-enforced areas (90th percentile of inspections), b) the impact of the internet in tech-intensive industries in weakly-enforced areas (10th percentile of inspections), and c) the differential impact of the internet in strict versus weak enforcement environments (the difference between (a) and (b)) in the bottom half of the table, highlighted in bold. Alongside, we report the corresponding F-statistics for the null hypothesis that the total effect is significantly different from zero. As in the previous section, we also report three columns, highlighting the addition of various controls, though we concentrate our analysis on the estimations with the most robust set of controls (columns (3) and (6)).

Concentrating on the impact of the internet in tech-intensive industries in high- relative to low-enforcement cities, we remark that the relative increases in local skill composition (cognitive and non-routine tasks) that we found in Table 5.1, in response to the local technology shock, resulted almost entirely from adjustments in heavy enforcement areas of the country. In fact, Appendix Table 3 reports skills results for the dependent variables in levels, and demonstrates that the decreases in employment associated with the technology shock were smallest among skilled workers in strictly-enforced municipalities, and largest among unskilled workers in weakly-enforced municipalities. This is consistent with the idea that skilled workers have a higher cost of adjustment—strong regulations stifle adjustment and particularly so for high-skilled workers.

Due to the enforcement bias in favor of skilled workers, we see that the shift in the composition of the workforce toward cognitive and non-routine tasks found in Table 5.1 in response to the technology shock is fully driven by changes in strong labor market regulatory environments. Policymakers often position and propose labor market policies to protect vulnerable workers. These results, however, are in stark contrast to these ideas. Counter to the best policy intentions, our evidence points to the idea that labor market regulations differentially benefit the skilled workforce.

5.3. Disaggregated tasks

We now ask whether our main findings, reported in Tables 5.1 and 5.2, hold for all types of cognitive, manual, non-routine, and routine tasks. As we discuss in Section 3.1, and outline in Tables 3.1 and 3.2, we decompose our broad task bundles into more refined task categories. Cognitively-oriented abilities can be analytical in nature (offering "mathematical reasoning") or communications-based, such as "oral expression". Similarly, among non-routine tasks, some require more problem-solving, cognitive skills, such as activities associated with “analyzing data or information”, while others are more manual in nature, like “inspecting equipment, structures, or material”.

Cognitive abilities Our main results suggest that technology favors cognitive tasks. Some cognitive skills require little to no interaction with other people and are highly analytical; activities similar to the ones this author is performing right now to write this paper—fluency of ideas and originality. Meanwhile, other cognitive skills require interaction and communication with others, such as those professions requiring oral expression and speech clarity. Despite the advances of computers, digital technology still has not yet fully mastered human interaction, suggesting that cognitive, interactive, and communications skills may be some of the most important individual skill sets as digital technologies advance.

Exactly which types of cognitive tasks do digital technologies support? Column (1) of Table 5.3 presents results for a regression of equation (1) when the dependent variable disaggregates cognitive tasks into those tasks that are analytical relative to those tasks that are communication-intensive among the set of cognitive tasks. The results offer some statistical support for a small shift toward interactive, communication-based tasks (among the cognitive tasks) in response to technological change, as is evidenced by the negative coefficient sum at the bottom of the table.

Column (1) of Table 5.4 also demonstrates the value of such tasks in a technologically-advancing economy. The shift toward communication-based cognitive skills occurs in tech-intensive industries located in strictly- and weakly-enforced municipalities; however, the effect is most pronounced in strong regulatory environments, suggesting that the employer-level costs of adjustment for such skills are particularly high.

Manual abilities Advances in digital technologies have allowed many manual tasks to be replaced by computers and automation. Tasks that require extreme precision and dexterity may be particularly susceptible to be substituted by computers, since the exact measurements can be codified, as compared to other manual tasks that might require more flexibility. We test this idea in column (2) of Table 5.3. Indeed, the results are supportive of the idea that precision-based manual tasks lose out in relation to other broad manual tasks in the aftermath of the technology shock. While we have no strong priors on how labor market regulations may interplay with precision versus other manual tasks, the empirical analysis in Table 5.4 suggests even stronger shifts toward other manual tasks, such as those requiring strength and flexibility in strictly-enforced municipalities.

Non-routine activities Even among non-routine tasks, some require more problem-solving, cognitive skills, such as activities associated with analyzing data or information, while others are more manual in nature, like inspecting equipment, structures, or material. In column (3) of Table 5.3, we report results from specification (1) with the relative cognitive-to-manual skill intensity within non-routine tasks. These results illustrate that the shift toward non-routine tasks is likely driven more by changes in routine tasks, than by changes within the set of non-routine tasks—the technology shock has no impact on the cognitive-to-manual task ratio within the set of non-routine tasks. The results in Table 5.4 further support this idea—there is very little statistical evidence that technology impacts the cognitively-oriented share of non-routine tasks in any area of the country—strictly-enforced or weakly-enforced.

Routine activities Controlling machines and processes is a routine activity that is highly manual, while documenting and recording information is a more cognitive, routine task. As reported in column (4) of Table 5.3, among routine tasks, routine, manual tasks also decline by more than routine, cognitive tasks, leading to an increase in the share of cognitive tasks within routine tasks. This is further support of the skill-biased nature of technological change. However, in contrast to our earlier results, there is no statistical skill bias in labor policy (Table 5.4) when comparing routine, cognitive tasks and routine, manual tasks. The results suggest that regulatory enforcement does not differentially impact the routine cognitive versus manual skill composition of tech-intensive industries.

5.4. Robustness checks

A key issue in our identification strategy relies on whether changes in the city-industry outcome variables for tech-intensive industries would have been the same had the internet never arrived in the city. We test this hypothesis by looking at the pre-internet trends in skill task indices across municipalities and industries. Table 5.5 reports results for two cross-sectional regressions relating the pre-reform change (1999-1996) in the cognitive-to-manual task ratio and the non-routine-to-routine task ratio, respectively in columns (1) and (2), to the timing of the provision of internet services, differentially for industries depending on their intensity of technology use. To be precise, PRO_{m1999}, for example, is a dummy variable equal to one if city m had adopted the internet by 1999, and comparatively for all other years. The omitted category refers to all cities which had not adopted internet services by 2006.

According to the results, cities with early provision of internet services (adopted in 1999) report no statistically different pre-trends than cities that had not adopted internet services by 2006 (the omitted category). Municipalities adopting in 2001, 2005, and 2006 are also statistically comparable in terms of pre-trends to municipalities that never saw the arrival of the internet during the sample period. Furthermore, the tech-intensive industries located in cities with early arrival of the internet compared to tech-intensive industries located in cities with no arrival of the internet report no statistically different pre-trends in our main dependent variables.

In another test for the validity of our results, we restrict the sample of cities to only those municipalities that had received internet by 2006. The identification of the main supply side technology shock is now based only on the timing of the technology adoption, abstracting from differences across municipalities in whether the internet had reached the city by 2006—not if there is internet, but when it arrived. Tables 5.6 and 5.7 report these results without and with the enforcement interactions, respectively, and confirm the main results in Tables 5.1 and 5.2. In fact, the magnitudes of the estimated effects are even larger.

7. Conclusions and Policy Implications

There is a strong concern around the globe that technology is increasingly replacing routine, manual tasks, displacing lower-skilled workers. Labor market institutions exist to protect workers from such shocks but, by increasing costs, labor policy may also constrain firms from adjusting the workforce to fully benefit from technology adoption. We assess the link between access to digital technologies and the demand for skills in the largest Latin American country. Between 1999 and 2006, Brazil underwent a period of strong growth in internet service provision, as well as increased enforcement of labor market regulations at the subnational level. Our empirical strategy exploits administrative data to assess the extent to which the adoption of digital technology affects the skill content of jobs at the local level. In addition, we investigate whether the stringency of labor regulations influences this adjustment, by comparing the effect across industries subject to different degrees of labor market regulatory enforcement.

Exploiting the fact that industries vary in the degree of reliance on digital technologies, our estimates suggest that digital technology adoption leads, in the short-run, to a reduction in employment in local labor markets. Tech-intensive industries reduce their reliance on both skilled and unskilled tasks in the aftermath of the technology shock, but the decrease in employment is larger for unskilled tasks, thereby shifting the composition of the workforce toward non-routine, cognitive skills. In contrast with labor policy intentions, our evidence points to the idea that labor market regulations differentially benefit the skilled workforce, particularly those workers employed in non-routine, cognitive tasks.

References

Acemoglu, Daron and David H. Autor (2011): "Skills, Tasks and Technologies: Implications for Employment and Earnings," in O. Ashenfelter and D. Card, **Handbook of Labor Economics**, Volume 4B, Amsterdam: North Holland.

Acemoglu, Daron and Pascual Restrepo (2017): "Robots and Jobs: Evidence from US Labor Markets," unpublished manuscript, Massachusetts Institute of Technology.

Ahsan, Ahmad and Carmen Pages (2009): "Are All Labor Regulations Equal? Evidence from Indian Manufacturing," *Journal of Comparative Economics*, 37 (1), pp. 62-75.

Akerman, Anders, Ingvil Gaarder, and Magne Mogstad (2015): "The Skill Complementarity of Broadband Internet," *The Quarterly Journal of Economics,* 130 (4), pp. 1781-1824.

Almeida, Rita K. and Pedro Carneiro (2009): "Enforcement of Labor Regulation and Firm Size," *Journal of Comparative Economics*, 37, pp. 28–46.

Almeida, Rita K. and Pedro Carneiro (2012): "Enforcement of Labor Regulation and Informality," *American Economic Journal: Applied Economics*, 4 (3), pp. 64-89.

Almeida, Rita K. and Jennifer P. Poole (2017): "Trade and labor reallocation with heterogeneous enforcement of labor regulations," *Journal of Development Economics*, *126*, pp. 154–166.

Almeida, Rita K., Ana M. Fernandes, Mariana Viollaz (2017): "Does the Adoption of Complex Software Impact Employment Composition and the Skill Content of Occupations? Evidence from Chilean Firms," World Bank Policy Research Working Paper No. 8110.

Autor, David H., Frank Levy, and Richard J. Murnane (2003): "The Skill Content of Recent Technological Change: An Empirical Exploration," *The Quarterly Journal of Economics*, 118 (4), pp. 1279-1333.

Bertola, Giuseppe, Tito Boeri, and Sandrine Cazes (2000): "Employment Protection in Industrialized Countries: The Case for New Indicators," *International Labour Review*, 139 (1), pp. 57-72.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan (2004): "How Much Should We Trust Difference-in-Differences Estimates?" *The Quarterly Journal of Economics*, 119 (1), pp. 249-275.

Böckerman, Petri, Seppo Laaksonen, and Jari Vainiomäki (2016): "Are Jobs More Polarized in ICT Firms?" IZA Discussion Paper Series No. 9851.

Brynjolfsson, Erik and Andrew McAfee (2011): **Race Against the Machine: How the Digital Revolution is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy**, Lexington: Digital Frontier Press.

Cardoso, Adalberto and Telma Lage (2007): **As Normas e os Fatos,** Rio de Janeiro: Editora FGV.

Dutz, Mark A., Lucas Ferreira Mation, Stephen D. O'Connell, and Robert D. Willig (2017): "Economywide and Sectoral Impacts on Workers of Brazil's Internet Rollout," World Bank Policy Research Working Paper No. 8042.

Goos, Maarten, Alan Manning, and Anna Salomons (2009): "Job Polarization in Europe," *American Economic Review*, *99* (2), pp. 58–63.

Goos, Maarten, Alan Manning, and Anna Salomons (2014): "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring," *American Economic Review*, 104 (8), pp. 2509-2526.

Heckman, James J. and Carmen Pages (2004): **Law and Employment: Lessons from Latin America and the Caribbean**, Chicago: The University of Chicago Press.

Hjort, Jonas and Jonas Poulson (2017): "The Arrival of Fast Internet and Skilled Job Creation in Africa," unpublished manuscript, Columbia Business School.

Kugler, Adriana (1999): "The Impact of Firing Costs on Turnover and Unemployment: Evidence from the Colombian Labor Market Reform," *International Tax and Public Finance Journal*, 6(3).

Kugler, Adriana and Maurice Kugler (2009): "Labor Market Effects of Payroll Taxes in Developing Countries: Evidence from Colombia," *Economic Development and Cultural Change*, 57 (2), pp. 335-358.

Maloney, William F. and Carlos Molina (2016): "Are Automation and Trade Polarizing Developing Country Labor Markets, Too?" World Bank Policy Research Working Paper No. 7922.

Messina, Julián, Giovanni Pica, and Ana Maria Oviedo (2016): "The Polarization Hypothesis in Latin America: How Demand Forces are Shaping Wage Inequality?" unpublished manuscript, Inter-American Development Bank.

Montenegro, Claudio E. and Carmen Pagés (2004): "Who Benefits from Labor Market Regulations? Chile, 1960-1998," in J. J. Heckman and C. Pagés, **Law and Employment: Lessons from Latin America and the Caribbean**, Chicago: The University of Chicago Press.

Muendler, Marc-Andreas (2002): “Definitions of Brazilian Mining and Manufacturing Sectors and Their Conversion,” unpublished manuscript, University of California, San Diego.

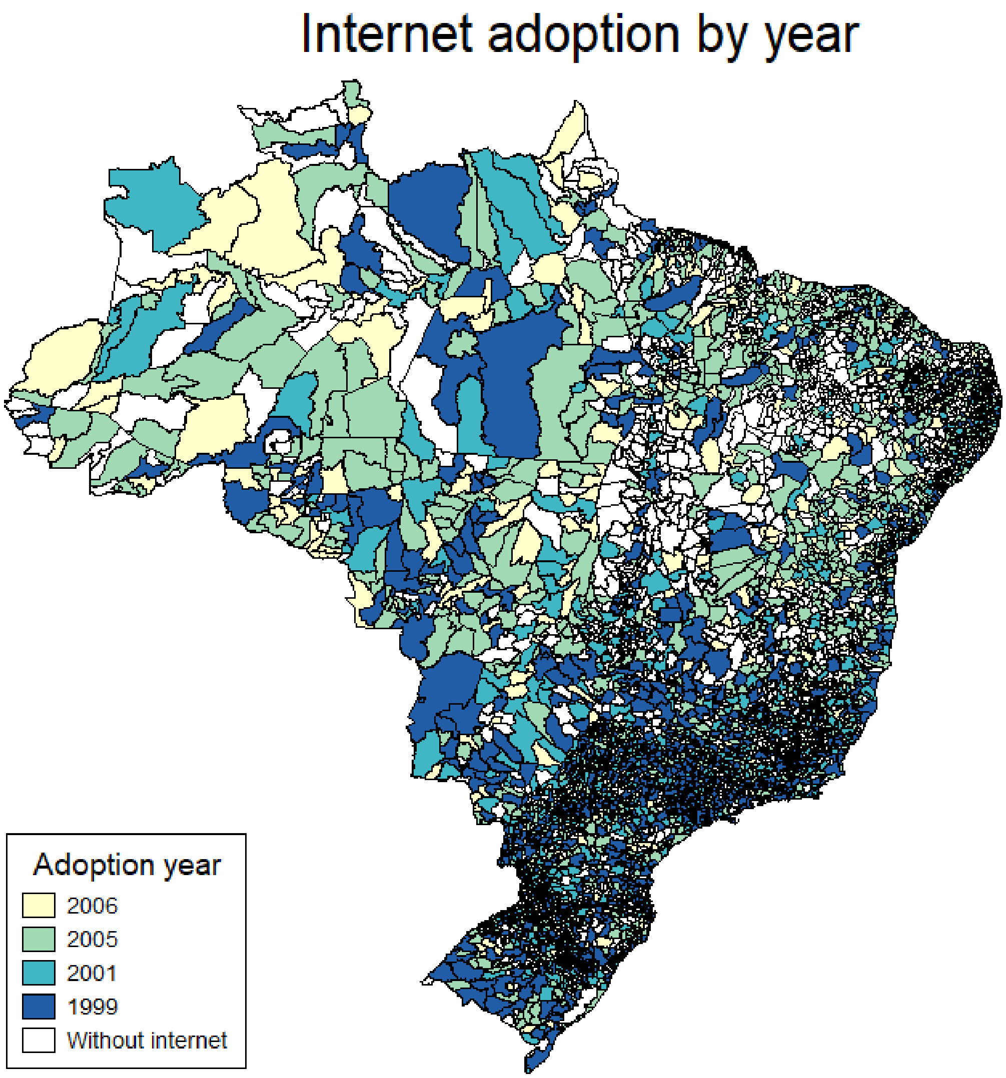
Muendler, Marc-Andreas, Jennifer P. Poole, Garey Ramey, and Tamara Wajnberg (2004): “Job concordances for Brazil: Mapping the *Classificação Brasileira de Ocupações* (CBO) to the International Standard Classification of Occupations (ISCO-88),” unpublished manuscript, University of California, San Diego.

Oldenski, Lindsay (2014): “Offshoring and the Polarization of the U.S. Labor Market,” *Industrial and Labor Relations Review*, 67.

Petrin, Amil and Jagadeesh Sivadasan (2013): “Estimating Lost Output from Allocative Inefficiency, with an Application to Chile and Firing Costs”, *The Review of Economics and Statistics*, 95 (1), pp. 286-301.

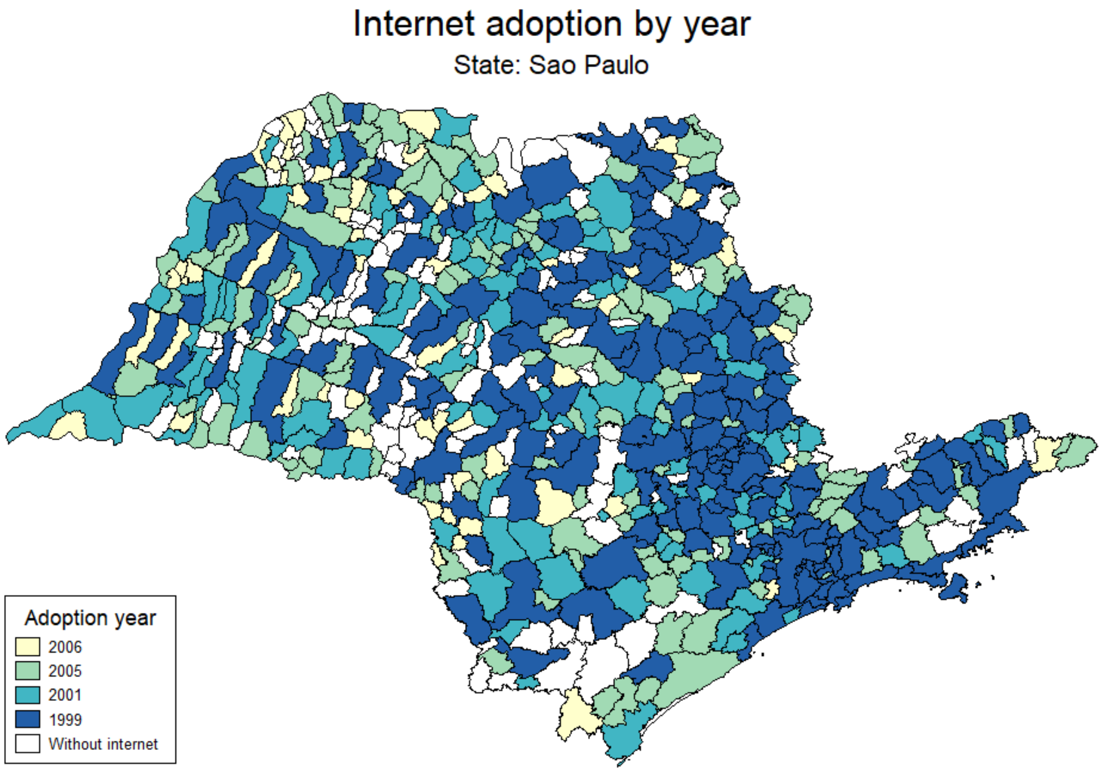
Riva, Flavio L. R. (2016): “Computerization, Occupational Tasks and the Labor Market: Evidence from a Natural Experiment in Brazil”. Dissertation. Escola de Economia de São Paulo.

Figure 3.1: Internet Service Provision, by Municipality



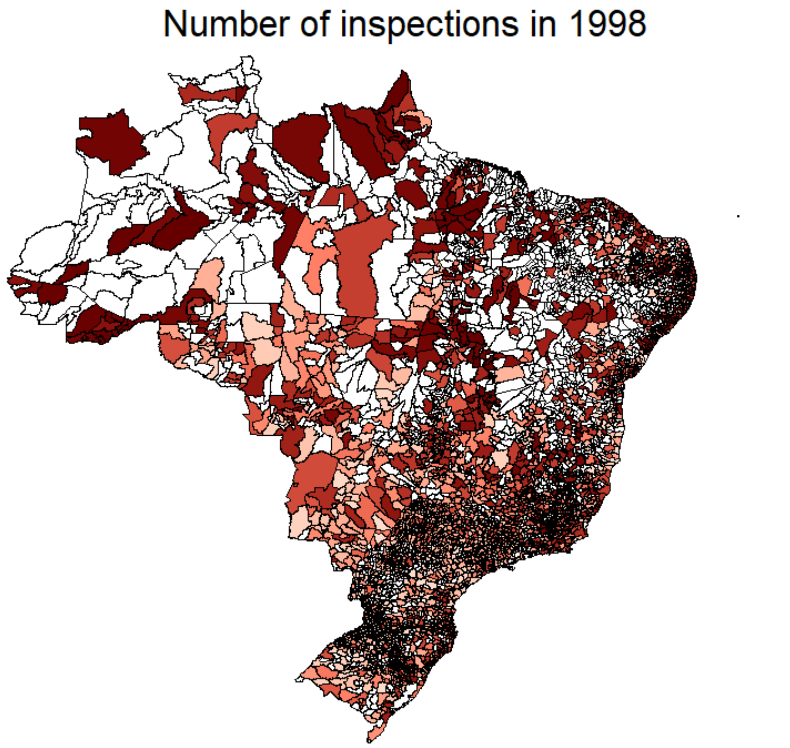
Source: IBGE.

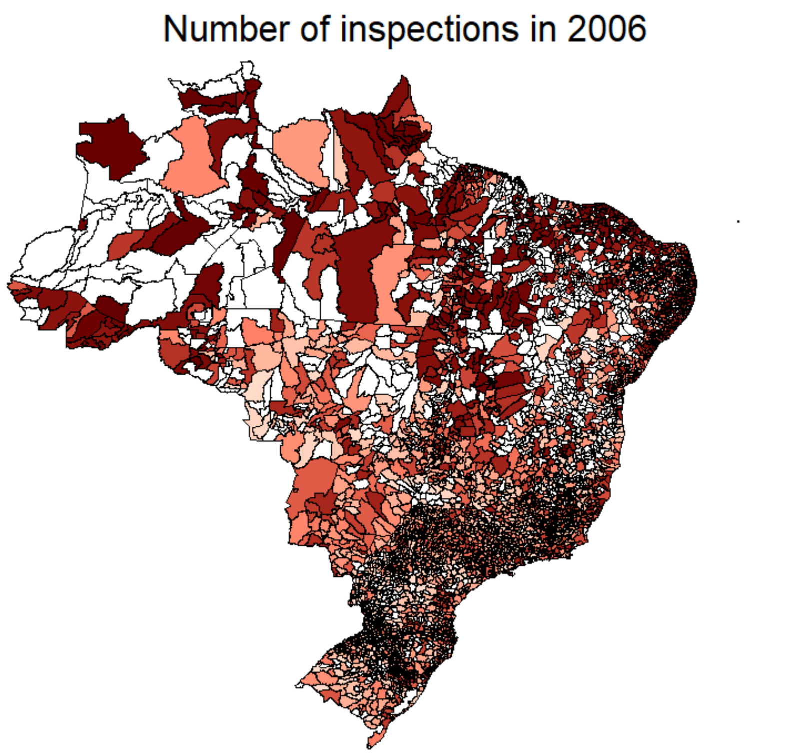
Figure 3.2: Internet Service Provision, by Municipality for São Paulo State



Source: IBGE.

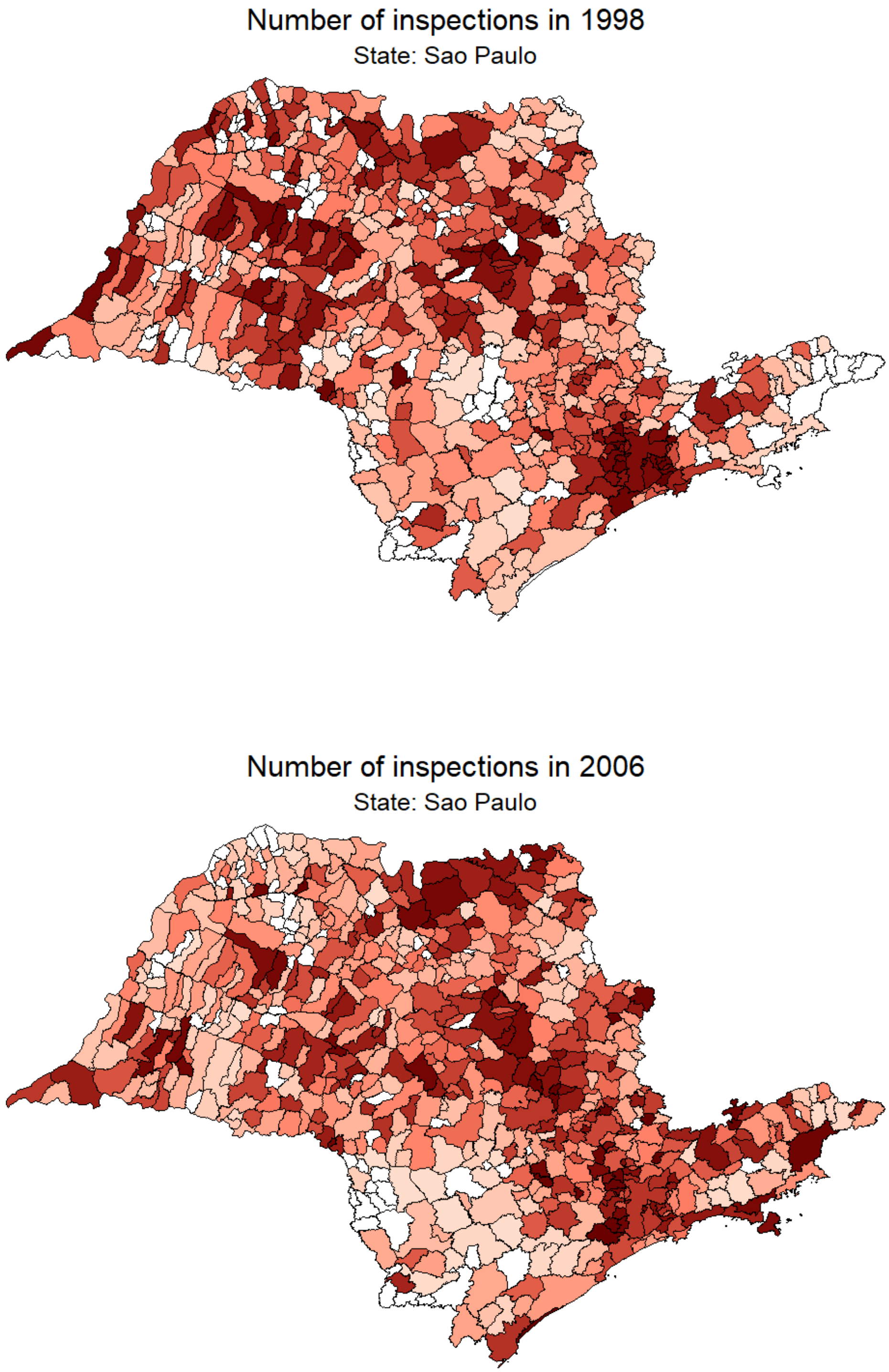
Figure 3.3: Labor Market Enforcement Intensity, by Municipality





Source: Ministry of Labor.

Figure 3.4: Labor Market Enforcement Intensity, by Municipality, São Paulo State



Source: Ministry of Labor.

Table 3.1: O*NET Abilities Classification

Manual Tasks		Cognitive Tasks	
Precision	Other	Analytical	Communication
Arm-Hand Steadiness	Reaction Time	Fluency of Ideas	Oral Comprehension
Manual Dexterity	Wrist-Finger Speed	Originality	Written Comprehension
Finger Dexterity	Speed of Limb Movement	Problem Sensitivity	Oral Expression
Control Precision	Static Strength	Deductive Reasoning	Written Expression
Multilimb Coordination	Explosive Strength	Inductive Reasoning	Speech Recognition
Response Orientation	Dynamic Strength	Information Ordering	Speech Clarity
Rate Control	Trunk Strength	Category Flexibility	
	Stamina	Mathematical Reasoning	
	Extent Flexibility	Number Facility	
	Dynamic Flexibility	Memorization	
	Gross Body Coordination	Speed of Closure	
	Gross Body Equilibrium	Flexibility of Closure	
	Near Vision	Perceptual Speed	
	Far Vision	Spatial Orientation	
	Visual Color Discrimination	Visualization	
	Night Vision	Selective Attention	
	Peripheral Vision	Time Sharing	
	Depth Perception		
	Glare Sensitivity		
	Hearing Sensitivity		
	Auditory Attention		
	Sound Localization		

Source: O*NET.

Table 3.2: O*NET Activities Classification

Routine Tasks		Non-Routine Tasks	
Manual	Cognitive	Manual	Cognitive
Performing General Physical Activities	Documenting/Recording Information	Inspecting Equipment, Structures, or Material	Evaluating Information to Determine Compliance with Standards
Handling and Moving Objects		Assisting and Caring for Others	Analyzing Data or Information
Controlling Machines and Processes		Operating Vehicles, Mechanized Devices, or Equipment	Interacting With Computers
Monitor Processes, Materials, or Surroundings		Repairing and Maintaining Mechanical Equipment	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
Monitoring and Controlling Resources		Repairing and Maintaining Electronic Equipment	Scheduling Work and Activities
			Getting Information
			Making Decisions and Solving Problems
			Thinking Creatively
			Updating and Using Relevant Knowledge
			Developing Objectives and Strategies
			Organizing, Planning, and Prioritizing Work
			Identifying Objects, Actions, and Events
			Estimating the Quantifiable Characteristics of Products, Events, or Information
			Judging the Qualities of Things, Services, or People
			Processing Information
			Interpreting the Meaning of Information for Others
			Establishing and Maintaining Interpersonal Relationships
			Selling or Influencing Others
			Resolving Conflicts and Negotiating with Others
			Coordinating the Work and Activities of Others
			Performing Administrative Activities
			Staffing Organizational Units
			Communicating with Supervisors, Peers, or Subordinates
			Communicating with Persons Outside Organization
			Performing for or Working Directly with the Public
			Developing and Building Teams
			Training and Teaching Others
			Guiding, Directing, and Motivating Subordinates
			Coaching and Developing Others
			Provide Consultation and Advice to Others

Source: O*NET.

Table 3.3: Average Task Indices, 1999-2006

	All Cities	City Internet Service		Industry Internet Use		Interaction	
		With	Without	High	Low	With Internet & High Tech	Without Internet & Low Tech
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Cognitive/Manual Tasks							
1999	0.98	0.99	0.86	1.15	0.83	1.15	0.79
2001	0.99	0.99	0.86	1.16	0.84	1.16	0.79
2005	0.98	0.99	0.83	1.18	0.82	1.18	0.76
2006	0.98	0.99	0.83	1.18	0.82	1.19	0.76
Panel B: Non-Routine/Routine Tasks							
1999	0.94	0.94	0.87	1.04	0.84	1.05	0.83
2001	0.94	0.94	0.86	1.05	0.84	1.05	0.82
2005	0.96	0.96	0.87	1.10	0.85	1.10	0.82
2006	0.96	0.96	0.87	1.10	0.85	1.10	0.83

Sources: O*NET; RAIS; IBGE; CPS.

Notes: Panel A reports the average task content in a city-industry cell as captured by the ratio of cognitive-to-manual tasks. Panel B reports the average task content in a city-industry cell as captured by the ratio of non-routine-to-routine tasks. Column (1) computes averages across all cities. Columns (2) and (3) report averages of the task ratios for cities with and without internet services, respectively. Columns (5) and (6) report averages of the task ratios for industries with high and low technological use (as measured by the median), respectively. Columns (6) and (7) report averages which most closely parallel our empirical strategy of the interaction of internet supply and technology use.

Table 3.4: Internet Service Provision, 1999-2006

	Share of Cities with Internet Services	Share of Population with Internet Services	Number of Cities with New Internet Services	Share of Cities with New Internet Services
	(1)	(2)	(3)	(4)
1999	0.15	0.61	-	-
2001	0.26	0.71	599	0.11
2005	0.51	0.84	1390	0.25
2006	0.61	0.88	555	0.10

Source: IBGE (1999-2006).

Notes: Column (1) reports the share of cities with internet services. Column (2) reports the share of the population that is covered by internet services. Column (3) reports the number of cities with new internet services in each year, and column (4) reports the share of cities with new internet services in each year.

Table 3.5: Enforcement of Labor Regulations, 1998-2006

	Share of Cities Inspected	Average Number of Inspections	Average Inspections Per 100 Registered Establishments in 1995	Standard Deviation of Inspections per 100 Registered Establishments in 1995
	(1)	(2)	(3)	(4)
1998	0.55	68.5	12	32
2000	0.62	81.5	18	44
2004	0.62	64.2	20	113
2006	0.67	72.5	23	83

Sources: Ministry of Labor administrative data on inspections (1998-2006); RAIS (1995).

Notes: Column (1) reports the share of cities inspected. Column (2) reports the average number of inspections. Column (3) divides the number of inspections in each city-sector by the number of registered establishments in the city-sector (as of 1995). Column (4) reports the standard deviation of the data reported in column (3).

Table 5.1: The Effects of Digital Technologies on Skills

	Panel A: Log (Cognitive/Manual Tasks)$_{mkt}$			Panel B: Log (Non-Routine/Routine Tasks)$_{mkt}$		
	Basic set of controls	Intermediate set of controls	Complete set of controls	Basic set of controls	Intermediate set of controls	Complete set of controls
	(1)	(2)	(3)	(4)	(5)	(6)
$PRO_{mt}*USE_k$	0.040***	0.043***	0.035***	0.075***	0.077***	0.068***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PRO_{mt}	-0.025***	-0.026***	-0.022***	-0.039***	-0.040***	-0.035***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Sector-State-Year Dummies	YES	YES	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES	YES	YES
City-Industry-Year Controls	NO	YES	YES	NO	YES	YES
Technology Controls	NO	NO	YES	NO	NO	YES
Impact of Internet in Tech-Intensive Industries	**0.015*** **	**0.017*** **	**0.014*** **	**0.036*** **	**0.037*** **	**0.033*** **
F-statistic	**16.3**	**21.6**	**13.4**	**114.7**	**123.3**	**99.0**
Observations	336,115	336,115	336,115	336,115	336,115	336,115

Sources: RAIS, O*NET, IBGE, CPS.

Notes: Columns (1) through (3) show the estimates of equation (1) using ordinary least squares, when the dependent variable is the city-sector-year average cognitive-to-manual task ratio for different sets of controls. Columns (4) through (6) show the estimates of equation (1) using ordinary least squares, when the dependent variable is the city-sector-year average of the non-routine-to-routine task ratio for different sets of controls. Columns (1) and (3) report the baseline specification, as reported in equation (1) in the text. Columns (2) and (4) add several city-industry-year controls (GDP, population, access to credit, gender, age, and educational composition of the workforce in the city, and exposure to global markets). Columns (3) and (6) also include the city-year rollout for local television and FM radio providers. Robust standard errors are clustered at the city-industry level. Our main parameter of interest is the overall impact of the internet in tech-intensive industries. This coefficient sum is reported in the bottom of the table in bold alongside the F-statistic testing the null hypothesis that the sum of the coefficients is equal to zero. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 5.2: The Effects of Digital Technologies on Skills, by Labor Regulatory Enforcement

	Panel A: Log (Cognitive/Manual Tasks)$_{mkt}$			Panel B: Log (Non-Routine/Routine Tasks)$_{mkt}$		
	Basic set of controls	Intermediate set of controls	Complete set of controls	Basic set of controls	Intermediate set of controls	Complete set of controls
	(1)	(2)	(3)	(4)	(5)	(6)
PRO_{mt}*USE_k	0.060***	0.066***	0.060***	0.112***	0.115***	0.100***
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
PRO_{mt}	-0.037***	-0.039***	-0.037***	-0.055***	-0.056***	-0.050***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ENF_{mKt-1}*PRO_{mt}*USE_k	0.014**	0.016**	0.018***	0.026***	0.027***	0.024***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
ENF_{mKt-1}*PRO_{mt}	-0.008**	-0.009***	-0.010***	-0.011***	-0.012***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ENF_{mKt-1}*USE_k	-0.012**	-0.013**	-0.016**	-0.019***	-0.019***	-0.029***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)
ENF_{mKt-1}	0.006**	0.007**	0.007**	0.008***	0.008***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Sector-State-Year Dummies	YES	YES	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES	YES	YES
City-Industry-Year Controls	NO	YES	YES	NO	YES	YES
Technology Controls with Enforcement Interactions	NO	NO	YES	NO	NO	YES
Impact of Internet in Tech-Intensive Industries						
Located in Cities at the 90th Percentile of Inspections	0.022***	0.026***	0.022***	0.053***	0.055***	0.047***
F-statistic	18.1	24.2	16.9	127.6	136.2	96.7
Located in Cities at the 10th Percentile of Inspections	0.005	0.006	0.002	0.012**	0.013**	0.012**
F-statistic	0.7	0.9	0.1	4.6	5.2	4.6
Difference in Impact of Internet in Tech-Intensive Industries						
90th Percentile - 10th Percentile of Inspections	**0.017***	**0.019****	**0.020****	**0.041*****	**0.042*****	**0.035*****
F-statistic	**3.3**	**4.5**	**4.5**	**27.0**	**28.4**	**18.0**
Observations	336,115	336,115	336,115	336,115	336,115	336,115

Sources: RAIS; O*NET; Ministry of Labor; IBGE; CPS.

Notes: Columns (1) through (3) show the estimates of equation (2) using ordinary least squares, when the dependent variable is the city-sector-year average cognitive-to-manual task ratio for different sets of controls. Columns (4) through (6) show the estimates of equation (2) using ordinary least squares, when the dependent variable is the city-sector-year average of the non-routine-to-routine task ratio for different sets of controls. Columns (1) and (3) report the baseline specification, as reported in equation (2) in the text. Columns (2) and (4) add several city-industry-year controls (GDP, population, access to credit, gender, age, and educational composition of the workforce in the city, and exposure to global markets). Columns (3) and (6) also include the city-year rollout for local television and FM radio providers. Robust standard errors are clustered at the city-industry level. Our main parameter of interest is the difference in the overall impact of the internet in tech-intensive industries located in strictly- versus weakly-enforced municipalities. This coefficient sum is reported in the bottom of the table in bold alongside the F-statistic testing the null hypothesis that the sum of the coefficients is equal to zero. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 5.3: The Effects of Digital Technologies on the Use of Specific Skills

	Cognitive Tasks	Manual Tasks	Non-Routine Tasks	Routine Tasks
	Log (Analytical/ Communication Tasks)$_{mkt}$	Log (Precision/ Other Manual Tasks)$_{mkt}$	Log (NR Cognitive/ NR Manual Tasks)$_{mkt}$	Log (R Cognitive/ R Manual Tasks)$_{mkt}$
	(1)	(2)	(3)	(4)
PRO_{mt}*USE_{k}	-0.045***	-0.048***	0.034***	0.046***
	(0.006)	(0.005)	(0.009)	(0.011)
PRO_{mt}	0.021***	0.014***	-0.027***	-0.027***
	(0.004)	(0.002)	(0.005)	(0.006)
Sector-State-Year Dummies	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES
City-Industry-Year Controls	YES	YES	YES	YES
Technology Controls	YES	YES	YES	YES
Impact of Internet in Tech-Intensive Industries	**-0.024*** **	**-0.034*** **	**0.007**	**0.019*** **
F-statistic	**59.5**	**125.6**	**2.3**	**2.3**
Observations	336,115	336,115	336,115	336,115

Sources: RAIS; O*NET; IBGE; CPS.

Notes: Columns (1) and (2) show the estimates of equation (1) in the text using ordinary least squares, where the dependent variables decompose the cognitive and manual abilities into city-industry-year analytical-to-communication task ratios and the city-industry-year precision-to-other manual task ratios, respectively. Columns (3) and (4) report the estimates of equation (1) using ordinary least squares, where the dependent variables decompose the non-routine and routine activities into city-industry-year non-routine-cognitive-to-non-routine-maunal task ratios and city-industry-year routine-cognitive-to-routine-manual task ratios, respectively. Robust standard errors are clustered at the city-industry level. All regressions include the most complete set of controls as specified in Table 5.1, columns (3) and (6). Our main parameter of interest is the overall impact of the internet in tech-intensive industries. This coefficient sum is reported in the bottom of the table in bold alongside the F-statistic testing the null hypothesis that the sum of the coefficients is equal to zero. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 5.4: The Effects of Digital Technologies on the Use of Specific Skills, by Labor Regulatory Enforcement

	Cognitive Tasks	Manual Tasks	Non-Routine Tasks	Routine Tasks
	Log (Analytical/ Communication Tasks)$_{mkt}$	Log (Precision/ Other Manual Tasks)$_{mkt}$	Log (NR Cognitive/ NR Manual Tasks)$_{mkt}$	Log (R Cognitive/ R Manual Tasks)$_{mkt}$
	(1)	(2)	(3)	(4)
PRO_{mt}*USE_k	-0.070***	-0.072***	0.034**	0.064***
	(0.010)	(0.008)	(0.013)	(0.017)
PRO_{mt}	0.036***	0.023***	-0.031***	-0.042***
	(0.006)	(0.003)	(0.007)	(0.010)
ENF_{mKt-1}*PRO_{mt}*USE_k	-0.018***	-0.019***	-0.001	0.013
	(0.005)	(0.004)	(0.007)	(0.009)
ENF_{mKt-1}*PRO_{mt}	0.011***	0.008***	-0.002	-0.010**
	(0.003)	(0.002)	(0.004)	(0.005)
ENF_{mKt-1}*USE_k	0.022***	0.030***	0.013*	-0.001
	(0.005)	(0.004)	(0.007)	(0.009)
ENF_{mKt-1}	-0.010***	-0.013***	-0.006	0.002
	(0.003)	(0.002)	(0.004)	(0.005)
Sector-State-Year Dummies	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES
City-Industry-Year Controls	YES	YES	YES	YES
Technology Controls with Enforcement Interactions	YES	YES	YES	YES
Impact of Internet in Tech-Intensive Industries				
Located in Cities at the 90th Percentile of Inspections	-0.032***	-0.046***	0.004	0.022***
F-statistic	49.9	125.1	0.4	7.5
Located in Cities at the 10th Percentile of Inspections	-0.011**	-0.014***	0.013*	0.016
F-statistic	4.5	10.6	3.0	2.6
Difference in Impact of Internet in Tech-Intensive Industries				
90th Percentile - 10th Percentile of Inspections	**-0.021*** **	**-0.032*** **	**-0.009**	**0.006**
F-statistic	**7.3**	**27.1**	**0.8**	**0.2**
Observations	336,115	336,115	336,115	336,115

Sources: RAIS; O*NET; Ministry of Labor; IBGE; CPS.

Notes: Columns (1) and (2) show the estimates of equation (2) in the text using ordinary least squares, where the dependent variables decompose the cognitive and manual abilities into city-industry-year analytical-to-communication task ratios and the city-industry-year precision-to-other manual task ratios, respectively. Columns (3) and (4) report the estimates of equation (2) using ordinary least squares, where the dependent variables decompose the non-routine and routine activities into city-industry-year non-routine-cognitive-to-non-routine-maunal task ratios and city-industry-year routine-cognitive-to-routine-manual task ratios, respectively. Robust standard errors are clustered at the city-industry level. All regressions include the most complete set of controls as specified in Table 5.2, columns (3) and (6). Our main parameter of interest is the difference in the overall impact of the internet in tech-intensive industries in strictly- versus weakly-enforced cities. This coefficient sum is reported in the bottom of the table in bold alongside the F-statistic testing the null hypothesis that the sum of the coefficients is equal to zero. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 5.5: Determinants of Pre-Reform Trends

Dep. Variable:	Log (Cognitive/ Manual Tasks)$_{mk\Delta 1999\text{-}1996}$ (1)	Log (Non-Routine/Routine Tasks)$_{mk\Delta 1999\text{-}1996}$ (2)
PRO_{m1999}	-0.004	0.004
	(0.005)	(0.004)
PRO_{m2001}	-0.005	-0.001
	(0.006)	(0.005)
PRO_{m2005}	-0.002	-0.005
	(0.008)	(0.007)
PRO_{m2006}	-0.006	-0.006
	(0.012)	(0.011)
PRO_{m1999}*USE_k	0.010	-0.008
	(0.007)	(0.006)
PRO_{m2001}*USE_k	0.015*	0.005
	(0.009)	(0.007)
PRO_{m2005}*USE_k	0.004	0.008
	(0.012)	(0.010)
PRO_{m2006}*USE_k	0.017	0.019
	(0.022)	(0.020)
Sector-State Dummies	YES	YES
Observations	64,488	64,488

Sources: RAIS, O*NET, IBGE, CPS.

Notes: Column (1) reports a regression where the dependent variable is the change, between 1996 and 1999, in the city-industry cognitive-to-manual task ratio. Column (2) reports a regression where the dependent variable is the change, between 1996 and 1999, in the city-industry non-routine-to-routine task ratio. In each regression, the explanatory variables include dummy variables capturing whether the city has internet services in each year and the interaction of these variables with a time-invariant measure of whether the industry uses technology intensively. The omitted category refers to the cities that had not adopted internet services by 2006. The cross-sectional regressions also include sector-state dummy variables. Robust standard errors are reported in parenthesis. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 5.6: Cities with Internet by 2006

	Log (Cognitive/ Manual Tasks)$_{mkt}$ (1)	Log (Non-Routine/Routine Tasks)$_{mkt}$ (2)
PRO_{mt}*USE_k	0.038***	0.072***
	(0.007)	(0.007)
PRO_{mt}	-0.023***	-0.036***
	(0.004)	(0.004)
Sector-State-Year Dummies	YES	YES
City-Industry Fixed Effects	YES	YES
City-Industry-Year Controls	YES	YES
Technology Controls	YES	YES
Impact of Internet in Tech-Intensive Industries	**0.015*** **	**0.036*** **
F-statistic	**15.6**	**110.7**
Observations	312,090	312,090

Sources: RAIS; O*NET; IBGE; CPS.

Notes: Column (1) shows the estimates of equation (1) using ordinary least squares when the dependent variable is the cognitive-to-manual task ratio. Column (2) shows the estimates of equation (1) using ordinary least squares when the dependent variable is the non-routine-to-routine task intensity. Robust standard errors are clustered at the city-industry level. The two regressions include the most complete set of controls as specified in Table 5.1, columns (3) and (6). Our main parameter of interest is the overall impact of the internet in tech-intensive industries. This coefficient sum is reported in the bottom of the table in bold alongside the F-statistic testing the null hypothesis that the sum of the coefficients is equal to zero. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Table 5.7: Cities with Internet by 2006, by Labor Regulatory Enforcement

	Log (Cognitive/ Manual Tasks)$_{mkt}$ (1)	Log (Non-Routine/Routine Tasks)$_{mkt}$ (2)
$PRO_{mt}*USE_k$	0.076***	0.114***
	(0.012)	(0.011)
PRO_{mt}	-0.043***	-0.055***
	(0.007)	(0.006)
$ENF_{mKt-1}*PRO_{mt}*USE_k$	0.026***	0.031***
	(0.007)	(0.006)
$ENF_{mKt-1}*PRO_{mt}$	-0.014***	-0.014***
	(0.004)	(0.003)
$ENF_{mKt-1}*USE_k$	-0.025***	-0.037***
	(0.007)	(0.006)
ENF_{mKt-1}	0.011***	0.014***
	(0.004)	(0.003)
Sector-State-Year Dummies	YES	YES
City-Industry Fixed Effects	YES	YES
City-Industry-Year Controls	YES	YES
Technology Controls with Enforcement Interactions	YES	YES
Impact of Internet in Tech-Intensive Industries		
Located in Cities at the 90th Percentile of Inspections	0.029***	0.055***
F-statistic	27.5	119.9
Located in Cities at the 10th Percentile of Inspections	-0.005	0.008
F-statistic	0.5	1.6
Difference in Impact of Internet in Tech-Intensive Industries		
90th Percentile - 10th Percentile of Inspections	**0.034*** **	**0.047*** **
F-statistic	**11.0**	**27.9**
Observations	312,090	312,090

Sources: RAIS; O*NET; Ministry of Labor; IBGE; CPS.

Notes: Column (1) shows the estimates of equation (2) using ordinary least squares when the dependent variable is the cognitive-to-manual task ratio. Column (2) shows the estimates of equation (2) using ordinary least squares when the dependent variable is the non-routine-to-routine task intensity. Robust standard errors are clustered at the city-industry level. The two regressions include the most complete set of controls as specified in Table 5.2, columns (3) and (6). Our main parameter of interest is the difference in the overall impact of the internet in tech-intensive industries located in strictly- versus weakly-enforced municipalities. This coefficient sum is reported in the bottom of the table in bold alongside the F-statistic testing the null hypothesis that the sum of the coefficients is equal to zero. *** significant at the 1 percent level; ** significant at the 5 percent level; * significant at the 10 percent level.

Appendix Table 1: Major Brazilian Occupations, by Broad O*NET Bundle

Abilities		**Activities**	
Manual Tasks	Cognitive Tasks	Routine Tasks	Non-Routine Tasks
Top 5			
Detonator	Chemical engineer (oil & rubber)	Car washer	Nurse
Professional diver (shallow and deep)	Chemical engineer	Bottle, glass, and other utensils washer	Surgical center nurse
Pyrotechnist	Chemical engineer (mining, metallurgy, steel, cement and ceramics)	Nurse	Nurse on board
Ammunition and explosives manufacture worker	Chemical engineer (paper and pulp)	Auditor nurse	Obstetric nurse
Steel cable worker	Chemical engineer (chemical industry)	Intensive care nurse	Intensive care nurse
Bottom 5			
History researcher	Recyclable material picker	Orchestrator	Carpet hand weaver
Political party leader	Household trash collector	Musician performer, instrumental	Fabric net weaver
Statistician (applied statistics)	Plasterer	Musicologist	Hand knitter
Theoretical statistician	Roof tiler (metal tiles)	Musician performer, singer	Weaver (hand loom)
Statistician	Roof tiler (cement-asbestos tiles)	Conductor musician	Hatter (straw hats)

Sources: O*NET; RAIS.

Appendix Table 2: The Effects of Digital Technologies on Skills (Levels)

Dep. Variable:	Log (Cognitive Tasks)$_{mkt}$	Log (Manual Tasks)$_{mkt}$	Log (Non-Routine Tasks)$_{mkt}$	Log (Routine Tasks)$_{mkt}$
PRO_{mt}*USE_k	-0.145***	-0.180***	-0.113***	-0.181***
	(0.013)	(0.013)	(0.013)	(0.013)
PRO_{mt}	0.092***	0.114***	0.082***	0.117***
	(0.008)	(0.008)	(0.008)	(0.008)
Number of Obs.	336,115	336,115	336,115	336,115
Impact of Internet in Tech-Intensive Industries	**-0.053*** **	**-0.066*** **	**-0.031*** **	**-0.064*** **
F-statistic	**84.1**	**112.3**	**27.7**	**115.7**
Sector-State-Year Dummies	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES
City-Industry-Year Controls	YES	YES	YES	YES
Technology Controls	YES	YES	YES	YES

Sources: RAIS, O*NET, IBGE, CPS.

Appendix Table 3: Digital Technologies, Enforcement, and Skills (Levels)

Dep. Variable:	Log (Cognitive Tasks)$_{mkt}$	Log (Manual Tasks)$_{mkt}$	Log (Non-Routine Tasks)$_{mkt}$	Log (Routine Tasks)$_{mkt}$
$PRO_{mt}*USE_k$	-0.087***	-0.147***	-0.056***	-0.156***
	(0.019)	(0.019)	(0.018)	(0.018)
PRO_{mt}	0.060***	0.097***	0.053***	0.103***
	(0.011)	(0.011)	(0.011)	(0.011)
$ENF_{mKt-1}*PRO_{mt}*USE_k$	0.041***	0.023**	0.042***	0.018*
	(0.011)	(0.011)	(0.011)	(0.010)
$ENF_{mKt-1}*PRO_{mt}$	-0.022***	-0.012*	-0.020***	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)
$ENF_{mKt-1}*USE_k$	-0.067***	-0.051***	-0.076***	-0.048***
	(0.011)	(0.011)	(0.011)	(0.011)
ENF_{mKt-1}	0.035***	0.028***	0.037***	0.026***
	(0.006)	(0.006)	(0.006)	(0.006)
Number of Obs.	336,115	336,115	336,115	336,115
Impact of Internet in Tech-Intensive Industries				
Located in Cities at the 90th Percentile of Inspections	-0.032***	-0.054***	-0.0074	-0.055***
F-statistic	15.3	38.0	0.9	42.9
Located in Cities at the 10th Percentile of Inspections	-0.083***	-0.085***	-0.065***	-0.078***
F-statistic	67.8	60.2	40.9	58.1
Difference in Impact of Internet in Tech-Intensive Industries				
90th Percentile - 10th Percentile of Inspections	**0.051*** **	**0.031** **	**0.058*** **	**0.023**
F-statistic	**13.1**	**4.3**	**16.5**	**2.6**
Sector-State-Year Dummies	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES
City-Industry-Year Controls	YES	YES	YES	YES
Technology Controls with Enforcement Interactions	YES	YES	YES	YES

Sources: RAIS; O*NET; Ministry of Labor; IBGE; CPS.