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

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There is a strong concern that technology is increasingly replacing routine tasks, displacing lower-skilled workers. Labor market institutions exist to protect workers from shocks but, by increasing labor costs, labor policy may also constrain firms from adjusting the workforce and, hence, from fully benefiting from technology adoption. We assess the link between access to digital technologies and the demand for skills in the largest Latin American country, Brazil. Between 1996 and 2006, the country experienced a period of strong growth in internet service provision, as well as in the 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 employment and 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 enforcement of labor regulations. Using the fact that industries vary in the degree of reliance on digital technologies, our estimates suggest that digital technology adoption leads to a reduction in employment in local labor markets. The decrease in employment is larger for routine tasks, thereby shifting the composition of the workforce toward non-routine, cognitive skills. However, and 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.

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1. Introduction

Economists have long recognized the efficiency gains from technological change. However, there is also concern, in both developing and developed countries alike, that routine, manual tasks are increasingly being replaced by technology, displacing lower-skilled workers (Autor, Levy, and Murnane 2003). Policymakers must weigh the broad economic benefits from technology adoption against the potential costs to the domestic economy. The gains from a more productive and flexible economy in the long run may be accompanied by short-term costs for workers, in terms of unemployment, income volatility, and poverty risk. Labor market institutions, including employment protection regulations, exist to protect workers from shocks, but they also have the unintended consequence of increasing the cost of labor for businesses. We analyze the impact that digital technology adoption has on local employment opportunities and on the employment composition of different skill groups. We pay special attention to 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.

Our paper exploits administrative data for Brazil, a country that underwent a substantive, subnational, internet rollout, as well as significant increases in the enforcement of labor market regulations between 1996 and 2006. We first assess the extent to which the adoption of digital technology affects the overall demand for workers and different types of skills. Our empirical strategy exploits the fact that industries vary in their degree of reliance on digital technologies. In particular, industries that intensively use technology located in cities with early provision of internet services are most likely to adopt digital technologies. In addition, given the fact that *de facto* labor regulations are heterogeneous within the country[1], we also explore the role of social protections in influencing the impact of digital technology on labor demand and on the demand for different skills.

[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.

Theoretically, the expected signs of these impacts are ambiguous. First, the effect of technology on labor demand depends on the degree to which workers are substitutes or complements for technology. In addition, it also depends on the degree to which technology allows businesses to become more efficient and thus expand output and employment. Second, increased enforcement of regulations, on the one hand, raises the cost of maintaining a formal workforce, such that areas facing stricter enforcement will have increased difficulties in adjusting labor to technology shocks, limiting employment. On the other hand, labor laws purposefully improve job quality through worker protections, such that companies in strictly-enforced areas hire more, as workers view formal employment as a more attractive option than informal employment, and firms demand more workers to meet per-worker hour restrictions.

Our research linking access to digital technology and labor market outcomes is innovative for four main reasons. First, we exploit a matched employer-employee database from the Brazilian Ministry of Labor covering the formal-sector labor force, between 1996 and 2006, and match it with subnational data on the municipal rollout of internet service over time. According to data from the Brazilian Census Bureau on the provision of internet services in each municipality, our time-period covers a significant expansion of internet services throughout the Brazilian economy. To our knowledge, we are the first to explore this unique data set with time-series and within-country variation in access to digital technologies.[2] Second, the administrative data allow us to analyze the impacts of digital technology adoption on the overall levels of employment at the city and industry level, across broad sectors and regions of the country. Third, we exploit a unique concordance between the Brazilian Classification of Occupations (CBO) and the U.S. Department of Labor's Occupational Information Network (O*NET) to assign a numerical index capturing the importance of distinct "activities" in each occupation. These skill indices allow us to construct measures of “routine” tasks and “non-routine” tasks used in each occupation. With these variables, we calculate each municipality-by-industry’s average task intensity across

[2] Dutz, et al. (2017) rely on a different database from Brazil to consider internet rollout over time and across municipalities in the country.

its workforce as the main dependent variables. Fourth, we match this data with 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).

Our empirical strategy to estimate the effect of digital technologies on employment and the demand for skills relies on substantial variation across municipalities and over time. The fact that the internet rollout varied across municipalities and over time makes it possible to control for municipality-specific and time-specific effects. We interact this main supply-side technology variable with industry-specific information on the demand for information and communications technology, relying on data from the *Current Population Survey* computer supplement, which asks workers whether they use a computer at their job. 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. 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.

Our work significantly contributes to a growing literature. While we are not the first to investigate the impact of digital technology on employment and the task content of occupations using micro data[3], we are among the first papers to explore this question for an emerging economy.[4] Furthermore, to our knowledge we are the first paper allowing technology to impact industries differently depending on their exposure to labor market regulatory enforcement. Contrary to previous studies that rely on cross-country or across-state variation in existing *de jure* labor regulations[5], we explore the fact that Brazilian employers are exposed to varying degrees of *de facto* labor regulations, measured by the number of Ministry of Labor inspections per establishment in the city and broad sector.

[3] See, for example, Goos, Manning, and Salomons (2009), Böckerman, et al. (2016), and Akerman, et al. (2015) for research on industrialized countries.
[4] To our knowledge, the only other paper assessing the impact of technology adoption on employment and the skill content of jobs in a developing country context is Almeida, Fernandes, and Violaz (2017). 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.
[5] As examples, please see Besley and Burgess (2004) and Autor, Kerr, and Kugler (2007),

Especially in a developing country context where enforcement is not homogeneous, we argue exploring 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. We thus investigate the differential impact of digital technologies on labor demand and skills among otherwise identical industries facing different *de facto* enforcement of the labor law, based on their municipal location.

Our main findings suggest that the rollout of internet in Brazil between 1996 and 2006 is associated with firms saving on their labor resources. Notably, technology-intensive industries, across all sectors of the economy, reduce their relative reliance on routine tasks, thereby shifting the skill composition of industries and cities toward non-routine tasks. Among the set of non-routine tasks, tech-intensive industries 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. However, in contrast with labor policy intentions, our results suggest that labor market regulations differentially benefit the more skilled workforce, particularly those workers performing more non-routine and cognitive tasks.

The rest of this paper is organized as follows. Section 2 offers an overview of the main theoretical predictions, through the lens of the existing literature, relating technology adoption and the subnational enforcement of labor regulations to labor market outcomes. Section 3 presents the main data sets and provides detailed descriptive statistics. In Section 4, we present our main reduced-form empirical model, while sections 5 and 6 describe our main results for the effects of technology across distinct regulatory environments, respectively. We offer conclusions and policy implications in the final section.

2. Theoretical Predictions

Digital technologies are one of the main drivers of the world economy today. The impact of technology 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, the evidence is still scarce for emerging economies.

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.

In this section, we offer a brief overview of the theoretical arguments and empirical evidence linking labor market outcomes and technological change, relying heavily on existing literature. We also present a short summary of the theoretical predictions and empirical research on the labor market implications of regulatory enforcement. Generally speaking, we note that theory offers ambiguous predictions, and thus, these are inherently empirical research questions.

2.1. The effect of technical change on labor markets

Employment The effect of technology on overall labor demand is theoretically ambiguous. Technology allows producers to become more efficient. A more efficient production process may allow companies to save on labor resources, increasing the use of technological capital, reducing overall employment. On the other hand, the productivity advances associated with technological change offer the opportunity to expand production and output with given resources. These output expansion effects may eventually help companies increase employment opportunities.

De Stefano, et al. (2014) find no evidence of such an effect for firms in the United Kingdom. In their work, access to broadband internet infrastructure has no statistically significant effect on firm performance. Similarly, Dutz, et al. (2017) contend that increased internet access in Brazil had no statistically significant effect on aggregate employment, though the authors argue strongly that employment shifted toward sectors of the economy with more output expansion opportunities (and away from sectors with more limited expansion opportunities). Similarly, in Chile, Almeida, Fernandes, and Viollaz (2017) do not find evidence of a significant impact on overall employment in the medium run, following the adoption of complex software for client, production, and business management. By contrast, Iacovone and Pereira-Lopez (2017) find that information and communications technology adoption increases the overall level of employment in Mexican firms. For Argentina and Colombia, there is also evidence that digital technologies are associated at the firm level with larger firms (Bambrilla (2017) and Ospino (2017)).

Skills The theory considering the implications of technical change on employment shares across different skill groups is also theoretically ambiguous, depending on the degree to which workers are substitutes or complements for technology. For instance, 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.[6] 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.[7] The theory predicts that computers substitute for routine tasks and complement non-routine tasks. Therefore, the process of automation reduces the relative demand for routine tasks and raises the relative demand for non-routine tasks, contributing to job polarization by reducing employment opportunities in occupations that require routine tasks.

Therefore, though digital technologies can increase economic output, such technological change may leave some workers worse off (Brynjolfsson and McAfee 2011). Goos, Manning, and Salomons (2009) find evidence for such a relative decrease in routine tasks across many European Union countries. Böckerman, et al. (2016) also test the routinization hypothesis using data from Finland and conclude that the adoption of computers in the workplace changes the demand for tasks within the firm toward non-routine skills. Akerman, et al. (2015) find suggestive evidence that broadband internet adoption in Norway complements skilled workers in executing non-routine tasks and substitutes for unskilled workers performing routine tasks, consistent with the routinization hypothesis.

Research related to the routinization hypothesis in the developing world is scarce. Messina, et al. (2015) analyze the task content of jobs in Bolivia, Chile, Colombia, El Salvador, and Mexico. According to their analysis, only Chile shows possible job polarization.[8] This runs

[6] The authors argue that, in order to have a clear view about the effects of technical change on the labor market, it is important to propose a continuum of tasks. For this reason, the authors make a distinction between tasks and skills. Under this model, skill refers to the worker’s capability for performing various tasks. Workers with a given skill level can change their set of tasks in order to respond to changes in labor market conditions and technology.

[7] Like our work that follows, 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.

[8] The authors recognize that data constraints limit their results. Moreover, they are only able to present a snapshot of possible job polarization, because there was no information available in order to measure changes in polarization.

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 potential polarizing forces. Riva (2015) tests the routinization hypothesis by using the 1991 market liberalization of computers in Brazil as a natural experiment to generate exogenous variation in technological change, 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 (2016) 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. They use information on occupations to define skill levels, relying on standard aggregations that do not allow them to access the task content of a job, thus obstructing any attempt to test the routinization hypothesis any further.

2.2. Responses to labor market policy and enforcement

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

To our knowledge, there are no theoretical or empirical papers assessing the impacts of technology according to industries' 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 altered by enforcement—first, for employment levels and second, for the relative demand for skill.

Employment Increased enforcement has two potentially confounding effects, leading to an ambiguous prediction. 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 evidences 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 difficulties in adjusting labor to shocks. If technology is a negative employment shock, tech-intensive industries in strict enforcement localities decrease formal employment by more than similar companies located in weakly-enforced municipalities. If technology expands output, leading to a positive employment shock, strictly-enforced industries will increase formal employment by less than industries in weakly-enforced areas.

However, because labor laws mandate worker protections, as well as restrictions on the hours of work per worker, stricter enforcement of labor regulations increases job quality (from the perspective of the worker) and the number of workers required to perform a complete 24-hour shift (from the perspective of the employer). Therefore, stricter enforcement could also imply that firms are more likely to register informal workers, an effect that could partially offset the previous one. It is not clear which impact would dominate, but our prior is that enforcement of labor regulation at the subnational level will inhibit formal labor adjustment, following the adoption of digital technology.

Skills We argue the main theoretical predictions related to the impact of enforcement on skill composition depend on the relative cost to adjust labor across skill groups. 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. 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. If this effect dominates, 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 Descriptive Statistics

Our main data are administrative records from Brazil for formal-sector workers linked to their employers. We characterize the tasks required in each worker's occupation, based on data describing the activities of similar occupations in the United States. We then aggregate the information on employment and skill intensity by each industry-municipality-year cell. We merge these outcomes of interest to city-by-time information on the provision 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.

The sample period for analysis covers a significant expansion of digital technologies throughout the country, between 1996 and 2006. The fact that Brazil's internet rollout and regulatory enforcement vary across municipalities and over time allows us to examine the impact of digital technologies on labor demand and on the demand for tasks depending on the degree to which industries use information technology and face regulatory enforcement.

3.1. Matched employer-employee administrative data

We use data collected by the Brazilian Labor Ministry, which requires by law that all registered establishments report on their formal workforce in each year. This information has been collected in the administrative records *Relação Anual de Informações Sociais* (RAIS) since 1986. For our analysis, we use data from RAIS for the years 1996 through 2006, when we also have complementary information on regulatory enforcement and the provision of internet services.

The main benefit of the RAIS database is that both establishments and workers are uniquely identified. The data offer information on workers' skill levels, as defined by occupation and education, beyond many similar datasets, and also include the industry[9] and municipality of each establishment. We restrict observations as follows. First, we drop all data pertaining to the public sector and to the agricultural sector, as the Ministry of Labor has recognized issues of data quality pertaining to these two broad sectors of the economy. 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.

At the beginning of our sample in 1996, the main employer-employee dataset includes over 14 million workers employed in 2,192 different occupations in approximately 440,000 establishments, producing in 544 4-digit CNAE industries and located in 4,229 municipalities across Brazil. By the end of our sample period in 2006, Brazil's formal labor force had grown significantly to almost 22 million workers employed in 2,217 occupations across around 750,000 establishments, producing in 529 industries and located in 4,868 municipalities.

3.2. Occupation-specific task data

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

The U.S. Department of Labor surveys workers in all occupations about the activities performed in the occupation. These occupation-specific attributes are maintained in the Department of Labor's Occupational Information Network. Our paper utilizes this information from the year 2000 for approximately 800 occupations in the U.S. Standard Occupational Classification (SOC).

O*NET offers "importance scores" ranging between 1 and 5 for 41 different "activities" associated with an occupation. A score of 1 means that a given activity is "Not Important" to the occupation, while a score of 5 means that a given activity is "Extremely Important" to the occupation.[10] Our main assumption in using data from the United States is that the same activities are required in similar occupations in Brazil. Even if the levels of such activities may be different across the two countries, we argue that the ranking of the importance of such tasks in similar occupations will not drastically differ. For this reason, we rely on O*NET's importance scores of different activities in U.S. occupations to characterize activities in Brazilian occupations.[11]

In order to better interpret O*NET's ordinal importance score ranking across occupations, we standardize the scores into a normalized numerical index between 0 and 1, which relies on each occupation's share of employment in the pre-period year of 1995, following Peri and Sparber (2009). Denote the importance score for activity a in a 5-digit CBO occupation c by $S_{c,a}$ and the employment share of occupation c in 1995 by $E_{c,95}$. We begin with an ordered vector of scores for a particular activity. The first element corresponds to the score related to the occupation with the highest score within a specific activity, while the last element

[10] For instance, 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".

[11] 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 Brazilian classification of occupations found in RAIS. We calculate the simple average of importance scores in cases where there are multiple SOC codes matched to a single CBO code.

corresponds to the score related to the occupation with the lowest score within the same activity, such that:

$$\mathbf{S'}^a = [\text{argmax}\,\{S_{1,a}, \dots, S_{C,a}\}; \dots;\ \text{argmin}\,\{S_{1,a}, \dots, S_{C,a}\}].$$

The components of the vector are then normalized as follows:

$$S'^a_1 = 1;\ S'^a_2 = 1 - E_{1,95};\ S'^a_3 = S'^a_2 - E_{2,95}; \dots;\ S'^a_C = S'^a_{C-1} - E_{C-1,95}.$$

We implement this procedure for each of the 41 activities. The normalization allows us to speak to the relative importance of such a skill among Brazilian workers. For instance, a score of 0.05 suggests that only 5% of employed workers supply this skill less intensively, whereas a score of 0.95 suggests that few workers supply the skill more intensively.

Our interest in this paper is in how technology impacts routine, manual skills as compared to non-routine, cognitive skills; that is, our interest is in broader skill groupings than those described in the raw O*NET database. Therefore, we next aggregate across activities within a "bundle" for each occupation. We consider the following activity bundles: routine versus non-routine activities. Routine activities are further disaggregated into manual, routine activities and cognitive, routine activities. Non-routine activities are also further disaggregated into manual and cognitive activities. We then also distinguish between non-routine, cognitive activities that are analytical versus non-routine, cognitive activities that are interactive or communications-oriented. Table 3.1 displays our classification of the 41 O*NET activities into these six distinct bundles.

It is important to note that in contrast to some papers in the literature relying on O*NET data, we classify and make use of all O*NET activities, rather than hand-picking a select one or few. We believe this strengthens the value of our results. As evidence of a high-quality match, Table 3.2 reports the five Brazilian occupations with the strongest requirements for each broad activity bundle and the five Brazilian occupations with the weakest requirements for each broad activity bundle. Car washers and window washers are among the most routine occupations, while orchestral musicians and missionaries are among the least routine occupations in Brazil. By contrast, psychiatrists are highly non-routine task intensive and hand knitters are among the least non-routine task intensive occupations in Brazil.

Our main goal is to assess how intense such activity bundles are used by Brazilian establishments, firms, and industries, and whether the intensity changes over time in response to the adoption of digital technologies. The final step in calculating the dependent variables in our analysis 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 results as employers shift the workforce composition over time. In the first column of Table 3.3, we report average values across all establishments for the main dependent variable—the ratio of non-routine to routine tasks. We note that the relative value of non-routine to routine tasks is always less than one, signaling Brazil's comparative advantage in lower-skilled tasks due to an abundance of lower-skilled labor. However, over the ten-year time horizon, the relative importance of non-routine tasks in the workforce has steadily increased, by about two percentage points.

3.3. Digital technologies data

Rollout of internet services Beginning in 1999, the Brazilian Census Bureau (IBGE) has conducted an annual survey of all Brazilian municipalities, the *Pesquisa de Informações Básicas Municipais* (known as 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. Among these is a question regarding whether the city has a company that provides internet services. We assume that no Brazilian city had access to internet services in 1996.

Table 3.4 presents basic descriptive statistics for this variable. 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. 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 obtained internet services earlier than the lighter areas on the map. The white municipalities in the center of the country and remote Amazon region are those cities that by 2014 remain without internet service. 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 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, we report the average non-routine-to-routine relative task intensity, conditioning on whether the city has internet service provision. Perhaps unsurprisingly, industries located in cities with internet access consistently employ higher shares of workers in non-routine tasks. All cities—those with and without internet—report shifts toward non-routine tasks over time.

Industry-specific information technology intensity We rely on data from the U.S. Census Bureau's *Current Population Survey*, which in an October 2003 supplement asked households whether they use a computer at their current job. Aggregating across all workers within their reported industry categories, we calculate the share of workers in U.S. industries who report using a computer at work. This is our main measure of the industry's technological intensity following Oldenski (2014). 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. As with the O*NET data, our use of U.S. data assumes that while the levels of technology-intensity may be different for a given industry across the two countries, the ranking of industries by their information technology intensity is not different. 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, we report the average non-routine-to-routine relative task intensity, 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 non-routine tasks. The difference is increasing over time—tech-intensive industries employ relatively greater shares of non-routine skills over time as compared to non-tech-intensive industries. Our empirical strategy exploits both this demand side use of technology as well as the supply side access to technology to identify the technology shock.

3.4. Enforcement data

Changes to the Brazilian Federal Constitution labor law in 1988 were very favorable to workers.[12] Following these changes in the labor code, the cost of labor to employers increased. First, the employer's payroll contribution increased from 18% to 20%. Second, the penalty on the plant for dismissing the worker without cause increased from 10% to 40% of the total contributions to the severance fund, *Fundo de Garantia do Tempo de Serviço*

[12] First, it reduced the maximum weekly working period from 48 to 44 hours. Second, it increased the overtime wage premium from 20% to 50% of the regular wage. Third, the maximum number of hours for a continuous work shift dropped from 8 to 6 hours. Fourth, maternity leave increased from 3 to 4 months. Finally, it increased one month's vacation time pay from 1 to 4/3 of a monthly wage.

(FGTS).[13] Employers in Brazil must also give advanced notice to workers in order to terminate employment. 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.

These *de jure* labor regulations are effective throughout the country. However, as 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.[14] 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. In practice, almost all of the inspected establishments are formal because it is difficult to visit a company that is not registered, since there are no records of its activity. Most of the inspections and subsequent fines for infractions in Brazil are to ensure compliance with workers' formal registration in the 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 1996, 1998, 2000, 2002, 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.

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

[13] If the worker is dismissed without justification (with the exception of workers on a probationary period), the plant is fined and has to pay the worker 40% of the FGTS contributions.
[14] A comprehensive explanation of the enforcement of the labor regulation system and its importance in Brazil is given in Cardoso and Lage (2007).

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 data. 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 46 percent in 1996 to 67 percent in 2006. As inspectors reach more and more cities, the average number of inspections per city-sector decreased—from 82 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 the third column, 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 more than doubled—from 11 inspections per 100 registered establishments to 23 inspections per 100 registered establishments—between 1996 and 2006.

Our identification relies on the across-city and over-time variation in labor market regulatory enforcement. The standard deviation reported in the fourth column signals the 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 1996, with darker shades portraying higher numbers. The bottom panel depicts the same statistic for the year 2012. 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. Empirical Model

Our goal in this paper is to uncover how technology affects employment across different skill-groups. In addition, we consider the role of social protections in altering the effects of technology on employment and the demand for skills.

4.1. Baseline specification

We consider Brazil's internet rollout across cities and over time as the main technology shock and argue that a similar technology shock impacts industries differentially based on their reliance on information and communications technology. We begin with the following framework in mind:

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

where m indexes the municipal location, k indexes the (4-digit) industry, t indexes time, K denotes Brazil's 16 broad CNAE sectors, and s denotes the 37 states of the country. We relate the industry-city employment levels and task-intensity (y_{mkt}) to the city-by-time-varying supply side technology shock, the provision of local internet services in a city and year as reported by IBGE (denoted as PRO_{mt}). β_1 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. In this sense, we argue that a similar technology shock of new internet services impacts industries differently depending on whether they require information and communications technology services.

Our baseline estimation also 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 employment levels and workforce composition (and, hence, task intensity), 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 the control is absorbed into the fixed effects. The effect of technology is then identified using across-municipality differences in internet services provision over time for industries that differentially use information technology.

We also include state-sector-specific year dummies (δ_{Kst}) to control for the average effect of Brazil's many policy reforms over this time period which may vary by state and sector. 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.

Tech-intensive industries located in cities with early provision of the internet are more likely to adopt digital technologies. Therefore, in interpreting our results, we concentrate on the impact of digital technologies in tech-intensive industries ($\beta_1 + \beta_2$). As we discuss in Section 2, the expected sign on the sum of the coefficients is unclear when the outcome of interest is total municipality-industry employment. In the case that technology is labor-saving, allowing companies to produce the same amount with fewer workers than before, we expect a negative combined coefficient ($\beta_1 + \beta_2 < 0$). On the contrary, positive employment effects of technological change ($\beta_1 + \beta_2 > 0$) are expected, if increased efficiency enables companies to expand production. Following Acemoglu and Autor (2011), as well as much of the evidence from the developed world, we hypothesize that $\beta_1 + \beta_2 > 0$ when the dependent variable is the non-routine-to-routine relative task intensity, as employers use technology to replace routine tasks shifting the composition of the workforce toward non-routine tasks.

4.2. Enhanced specification

Equation (1) only considers the main technology shock. The degree to which employers adjust labor in response to such a shock depends on the stringency of 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. For this reason, we next adapt our baseline specification to include city-by-broad sector exposure to Ministry of Labor inspections as follows:

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

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

An important concern relates to the exogeneity of the variation in labor regulations across cities. In particular, enforcement 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 fact that specification (2) includes city-industry fixed effects 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 (Almeida and Poole 2017).

However, one could still question the exogeneity of changes in enforcement at the city-sector level. To the extent that these changes correlate with changes in labor market outcomes, our estimates may be biased. We note that our empirical methodology follows the program evaluation literature and relates quasi-exogenous technology changes to labor market outcomes over time, differentially for industries located in diverse policy environments—a triple-interaction effect. Like with 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.

In order 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:

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

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:

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

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 technology on labor market outcomes in different regulatory environments on this difference $(\gamma_1(s-w)+\gamma_2(s-w))$.

Recall from Section 2, there are two confounding effects of labor policy on levels of employment: the higher labor costs associated with stricter enforcement that may limit hiring and the impact on job quality improvements that induce formal work registrations (of otherwise informal workers). If the first effect dominates, otherwise identical companies facing stricter enforcement of the labor law have increased difficulties in adjusting labor to shocks, decreasing (increasing) formal employment by more (by less) than companies located in weakly-enforced municipalities. By contrast, when the latter effect dominates, in response to the same technology shock, we would expect to see a smaller (larger) decrease (increase) in employment in areas of the country exposed to stronger regulatory enforcement.

Considering the relative demand for skill as the outcome of interest, again the theory offers no solid projections. If labor policy intentions are confirmed, we expect that $\gamma_1(s-w)+\gamma_2(s-w)<0$ when the dependent variable is the non-routine-to-routine relative task intensity. If labor market regulations reduce employment opportunities for the unskilled at the benefit of the skilled, following research by Montenegro and Pages (2004), we predict that $\gamma_1(s-w)+\gamma_2(s-w)>0$ when the dependent variable is the non-routine-to-routine relative task intensity. In the first case, the enforcement of labor market regulations stifles employment reductions in response to technology by more for workers in routine tasks, thereby shifting the composition of the workforce toward routine tasks in strict labor market environments. In the second setting, the enforcement of labor market regulations stifles employment reductions in response to technology by less for workers in routine tasks, thereby shifting the composition of the workforce toward non-routine tasks even more in strict labor market environments.

5. Baseline Results on the Effects of Digital Technology

5.1. Employment

First, we investigate the impact of internet technology on total employment levels in the city-industry. Table 5.1 reports results of equation (1) estimated by ordinary least squares, with standard errors clustered at the interactive city-industry level (the same level used to define the fixed effects following Bertrand, et al. (2004)). The dependent variable is the logarithm of total formal-sector employment 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), or the sum of the coefficients ($\beta_1 + \beta_2$). This coefficient sum is reported in the bottom portion of the table, along with the corresponding F-statistic and p-value for the null hypothesis that the sum of the coefficients is equal to zero.

The results in column (1), pooling all broad sectors of the economy for an economy-wide analysis, point to a negative impact of digital technology on employment in tech-intensive industries, not only relative to non-tech-intensive industries (β_1), but also in absolute terms ($\beta_1 + \beta_2$). Digital technologies, like the internet, allow employers to save on labor resources, reducing employment, presumably due to enhanced productivity. These results are important as they confirm the idea that in the short run, technology adoption may lead to substantive employment losses at the local level.

The remaining columns of Table 5.1 show that the employment reductions associated with increased adoption of digital technologies are not driven by any particular broad sector of the economy. Rather, technology decreases employment in all four major sectors of the economy: manufacturing, services, construction, and wholesale and retail trade. The negative employment effects are strongest in the more non-tradeable sectors of the economy. This makes economic sense, relying on the argument that the potential for output expansion opportunities (and hence offsetting employment expansion) are far less in non-tradeable sectors of the economy like construction and wholesale and retail trade, offering a plausible explanation for the larger negative employment effects of technology in these sectors.[15]

5.2. Skills

We next consider whether skilled and unskilled workers face similar employment reductions. 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.[16]

Non-routine versus routine skills Table 5.2 reports results from the estimation of equation (1) with dependent variables related to the skill-content of occupations as described in Section 3.2. Notably, column (1) reports results for our main dependent variable, the relative non-routine-to-routine task intensity, as we discuss in Section 4.1. The main results confirm the 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, shifting the composition of the workforce toward non-routine tasks. This is evidenced in the statistically-significant and positive coefficient on the impact of technology in tech-intensive industries at the bottom of the first column.

Cognitive versus manual skills The previous paragraph documented that increased access to technology shifts the composition of employment toward non-routine tasks. We now ask whether these findings hold for all types of non-routine and routine tasks. As we discuss in Section 3.2, and outline in Table 3.1, we can decompose non-routine tasks and

[15] The decreases in total city-industry employment in response to technology could result either from decreases in the total number of establishments in the city and industry (the extensive margin) or from decreases in the average establishment size in the city-industry (the intensive margin). In unreported results, available by request, we find that technology reduces employment along both the extensive and intensive margin, though reductions in the intensive margin account for over 60 percent of the total decline in employment in all broad sectors of the economy except construction.

[16] From here forward, we consider only the economy-wide effects of technology and leave the unreported sector-by-sector results to be available by request.

routine tasks into those tasks requiring cognitive abilities and those tasks requiring manual abilities. For instance, 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. Controlling machines and processes is a routine activity that is highly manual, while documenting and recording information is a more cognitive, routine task.

In the second and third columns of Table 5.2, we report results from specification (1) with the relative cognitive-to-manual skill intensity within non-routine and within routine tasks, respectively. These results illustrate that the shift toward non-routine tasks is driven by the relative decline in the intensity of the manual tasks for both non routine and routine tasks. Non-routine, manual task intensity declines by more than non-routine, cognitive task intensity, shifting the composition of the non-routine workforce toward cognitive tasks. 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.

Analytical versus interactive skills Technology favors non-routine, cognitive tasks. Some non-routine, 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—analyzing data and information and interacting with computers. Meanwhile, there are other non-routine, cognitive skills that require interaction and communication with others—such as those professions requiring communicating with supervisors, peers, or subordinates or teaching and training others. Despite the advances of computers, digital technology still has not yet fully mastered human interaction, suggesting that non-routine, cognitive, interactive skills may be some of the most important individual skill sets as digital technologies advance.

Exactly which types of non-routine, cognitive tasks do digital technologies support? The final column of Table 5.2 presents results for a regression of equation (1) when the dependent variable disaggregates non-routine, cognitive tasks into those tasks that are analytical relative to those tasks that are interactive and communication-intensive among non-routine, cognitive tasks. The results offer some statistical support for a small shift toward interactive, communication based tasks (among the non-routine, cognitive tasks) in response to technological change, as is evidenced by the negative coefficient sum in the bottom of the table.

6. Heterogeneity of Impacts with Enforcement of Labor Regulations

In this section, we investigate the role of labor market regulatory enforcement, by discerning the effects of technology by the location of the employer.

6.1. Employment

Table 6.1 reports coefficients from the estimation of equation (2) by ordinary least squares with standard errors clustered at the interactive city-by-industry level, across all broad sectors of the economy. 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 (90^{th} percentile of inspections), b) the impact of the internet in tech-intensive industries in weakly-enforced areas (10^{th} 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. Alongside, we report the corresponding F-statistics and p-values for the null hypothesis that the total effect is significantly different from zero.

Concentrating on the impact of the internet in tech-intensive industries in high- relative to low-enforcement cities (highlighted in bold at the bottom of the table), across all broad sectors of the economy (first column), we find that the decreases in employment in response to technology in tech-intensive industries located in strictly-enforced municipalities are not statistically distinguishable from the decreases in employment in response to technology in otherwise identical tech-intensive industries located in weakly-enforced municipalities. Industries in all areas of the country experience decreases in employment in response to presumably labor-saving technological change. Recall from Section 4 that there are two potentially offsetting effects of enforcement on employment—it is likely that these countervailing effects of enforcement largely balance out in the aggregate economy. This is also the case in the services sector.

By contrast, in the manufacturing sector, the decreases in employment in tech-intensive industries in response to digital technologies like the internet is wholly explained by decreases in employment in tech-intensive industries in strictly-enforced areas. This is consistent with work in Almeida and Carneiro (2009), Almeida and Carneiro (2012), and Almeida and Poole (2017) which document lower employment in heavily-regulated areas, as high labor costs induce firms to hire less. The employment responses to technology in construction companies in heavily-inspected areas also face a strong differential decrease as compared to equal construction companies in weakly-enforced areas. Interestingly, employment differentially increases in response to the internet shock in tech-intensive wholesale and retail trade industries faced with higher inspections, perhaps due to increased formal work registration or shorter per-worker hours in that sector.

6.2. Skills

Do labor policies matter to companies as they adjust the workforce toward non-routine tasks in response to the technology shock?

Non-routine versus routine skills Table 6.2 reports results from the estimation of equation (2), with the dependent variables as in Table 5.2. We focus in the first column on the relative non-routine-to-routine task intensity in the city and industry. Once again, we concentrate our analysis on the difference in the impact of the internet in tech-intensive industries located in cities at the 90th percentile of enforcement relative to otherwise identical industries located in cities at the 10th percentile of enforcement (highlighted in bold at the bottom of the table). We learned in Table 6.1 that the decrease in employment in response to advances in technology occurred in both strictly-enforced and weakly-enforced cities. Table 6.2 clearly demonstrates that the decrease in employment as a result of increased access to the internet in heavy enforcement areas of the country is solely driven by decreases in employment of unskilled workers performing routine tasks. This is consistent with evidence as reported in Montenegro and Pages (2004).

Due to the enforcement bias in favor of skilled workers, we see that the shift in the composition of the workforce toward non-routine tasks found in Table 5.2 in response to the technology shock is wholly driven by changes in strong labor market regulatory environments. Policy-makers often position and propose labor market policies to protect vulnerable workers. These results 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.

Cognitive versus manual skills The previous paragraphs documented that increased access to technology shifts the composition of employment toward non-routine tasks, even more so in strict regulatory environments. In the next columns of Table 6.2, we show this result holds across all types of non-routine and routine skills. Within non-routine tasks and within routine tasks, in all regulatory environments, technological change shifts the composition of the workforce toward skilled (cognitive) tasks and away from unskilled (manual) tasks.

Interestingly, the shift toward non-routine, cognitive tasks and away from non-routine, manual tasks is larger in weakly-regulated municipalities as compared to otherwise identical tech-intensive industries in strongly-regulated municipalities. Despite the strong evidence in favor of skill-biased regulations in the previous section, these results offer some evidence that employment protections are helping middle-skilled workers—those workers who perform non-routine, but manual tasks. By contrast, there is no statistical skill bias in labor policy 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.

Analytical versus interactive skills Labor market regulations tend to favor workers employed in the middle of the skill distribution—those workers employed in non-routine, manual tasks. Even still, in the final column of Table 5.2, we consider whether labor market regulations promote certain non-routine, cognitive tasks over others? The answer is a clear no.

7. Conclusions and Policy Implications

There is a strong concern around the globe that technology is increasingly replacing routine tasks, displacing lower-skilled workers. Labor market institutions exist to protect workers from 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, Brazil. Between 1996 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 employment and 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 non-routine and routine tasks in the aftermath of the technology shock, but the decrease in employment is larger for routine 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

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Figure 3.1: Internet Service Provision, by Municipality

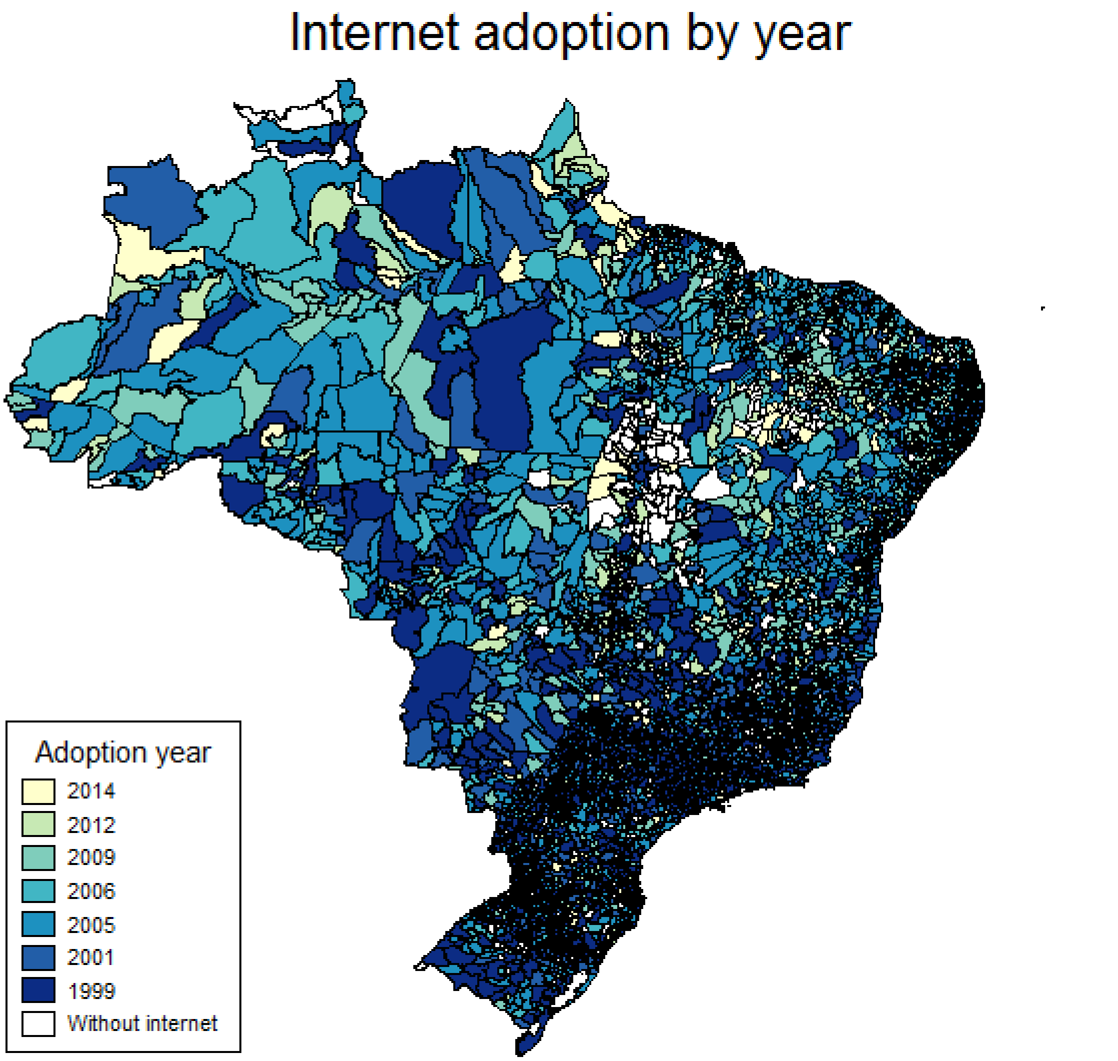

Figure 3.2: Internet Service Provision, by Municipality for São Paulo State

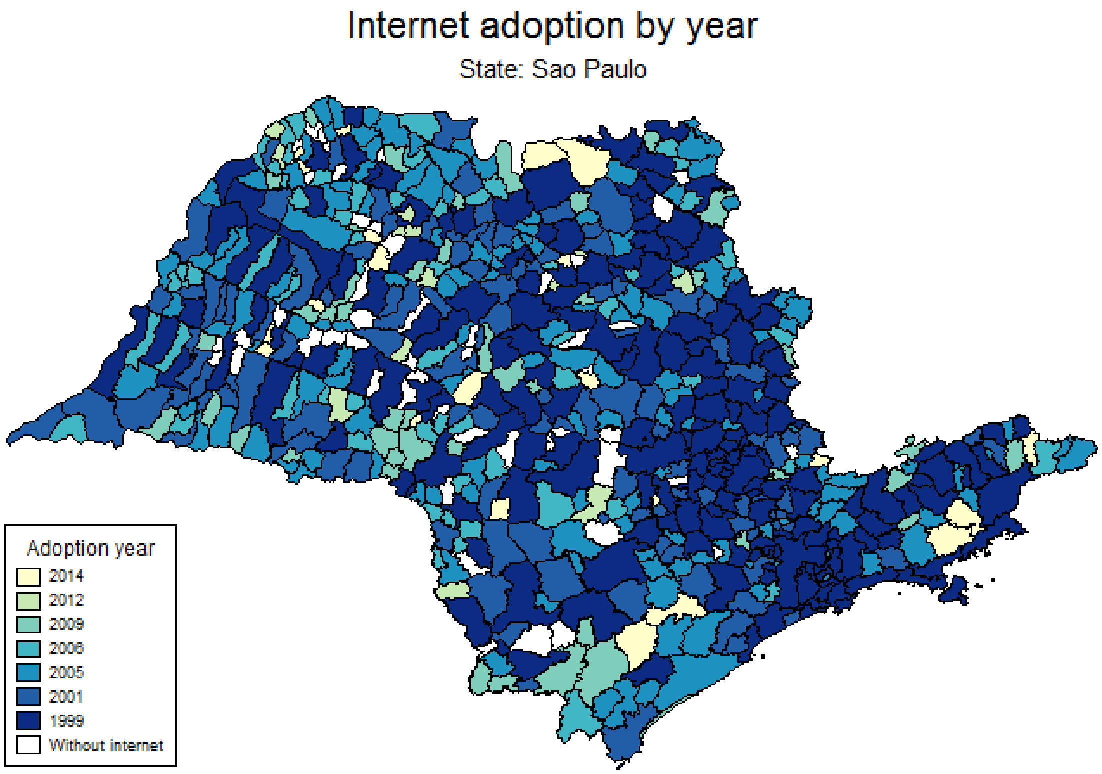

Figure 3.3: Labor Market Enforcement Intensity, by Municipality

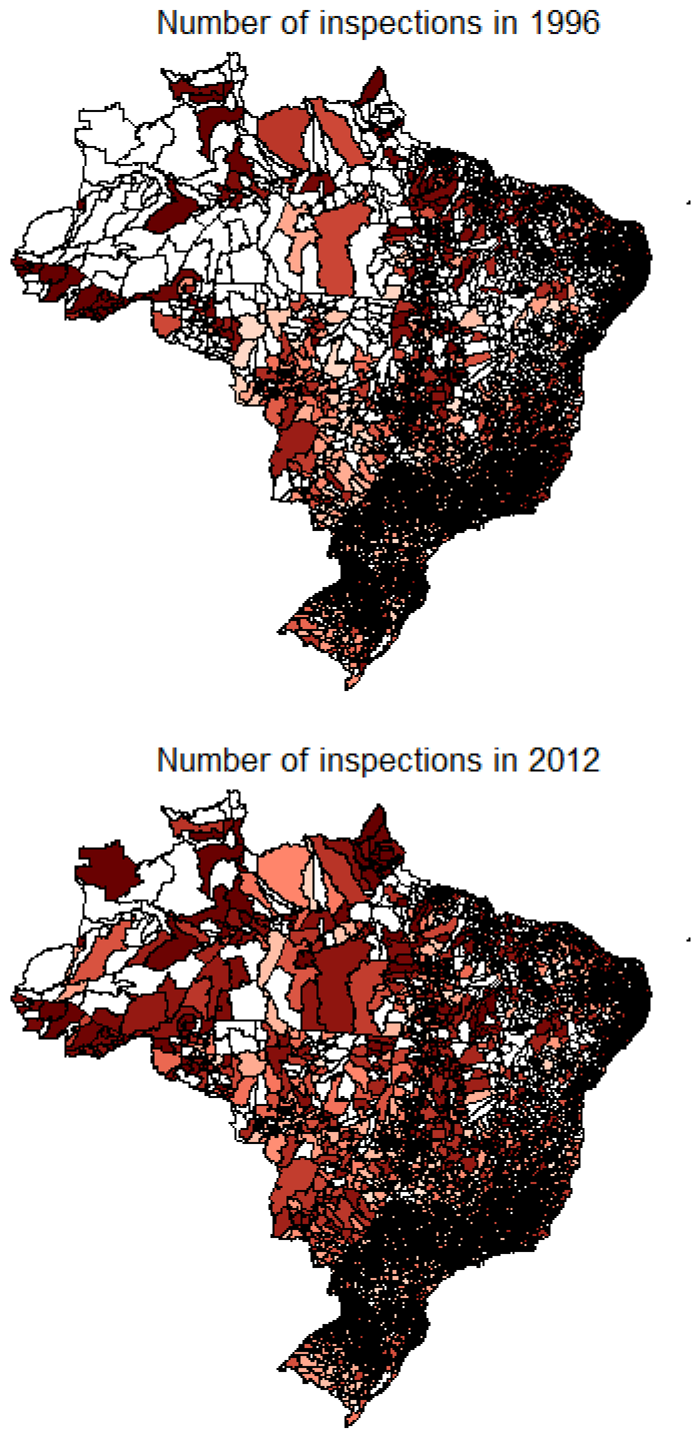

Figure 3.4: Labor Market Enforcement Intensity, by Municipality, São Paulo State

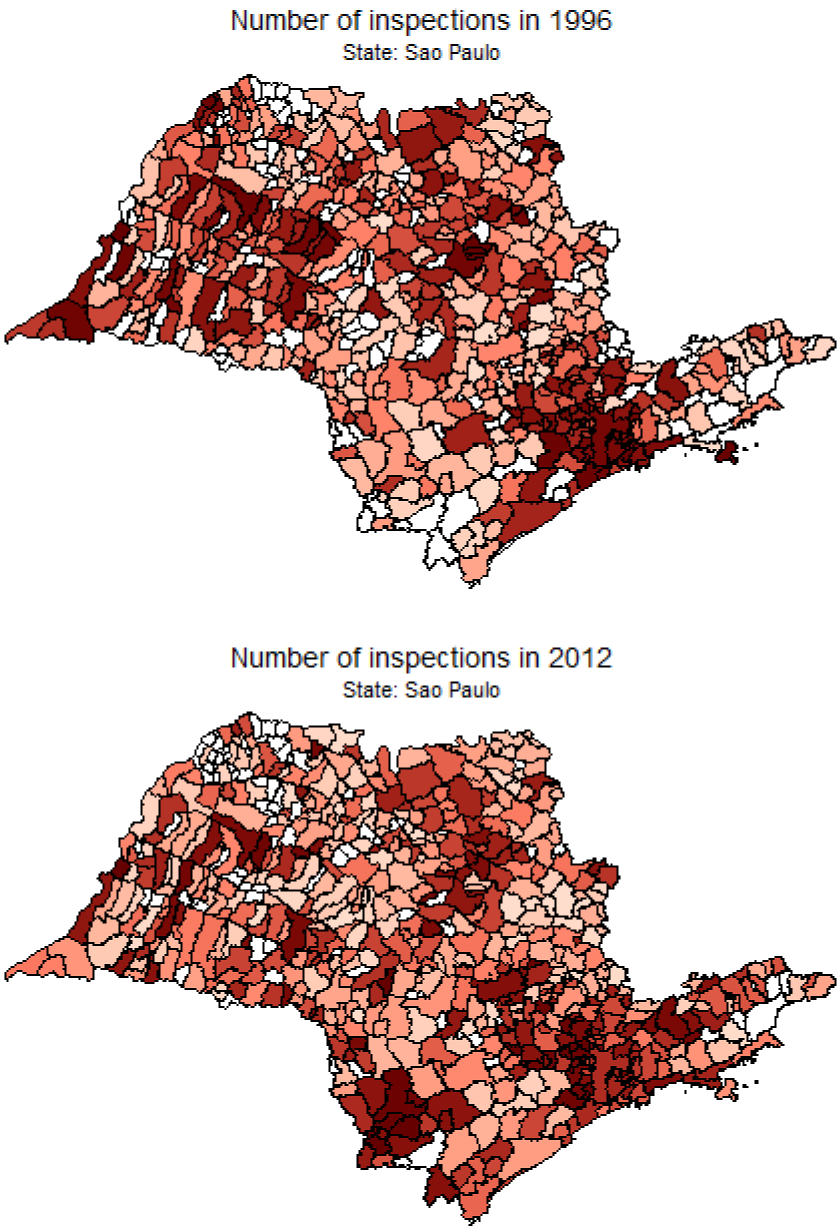

Table 3.1: O*NET Activities Classification

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

Table 3.2: Major Brazilian Occupations, by Broad O*NET Bundle

ROUTINE TASKS	NON-ROUTINE TASKS
Top 5	
LAVADOR DE VEICULOS	ENFERMEIRO PSIQUIATRICO
LIMPADOR DE JANELAS	ENFERMEIRO EM GERAL
ENFERMEIRO DE TERAPIA INTENSIVA	ENFERMEIRO DE TERAPIA INTENSIVA
ENFERMEIRO EM GERAL	ENFERMEIRO DE CENTRO CIRURGICO
OUTROS ENFERMEIROS	ENFERMEIRO DO TRABALHO
Bottom 5	
TEOLOGO	TECELAO (TEAR MANUAL)
OUTROS MEMBROS DE CULTO RELIGIOSO E TRAB ASSEMELHADOS	OUTROS TECELOES
MINISTRO DE CULTO RELIGIOSO	CROCHETEIRO , A MAO
MISSIONARIO	TRICOTEIRO , A MAO
ORQUESTRADOR	PICOTADOR DE CARTOES JACQUARD

Table 3.3: Non-Routine/Routine Task Intensity, 1996-2006

	Average Non-Routine/ Routine Task Intensity	City-Level Internet Service		Industry-Level Internet Use	
		With	Without	High	Low
1996	0.92			1.01	0.85
1999	0.93	0.96	0.86	1.02	0.85
2001	0.93	0.96	0.86	1.02	0.85
2005	0.94	0.97	0.88	1.10	0.85
2006	0.94	0.98	0.90	1.10	0.85

Sources:

Note:

Table 3.4: Internet Service Provision, 1999-2006

	Share of Cities with Internet Services	Share of Population with Internet Services	Number of New Cities with Internet Services	Share of Cities with New Internet Services
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

Sources: IBGE (1999-2014).

Note: This table reports different statistics at the city level between 1999 and 2014. Column (1) reports the number of cities with reported data in that year. Column (2) reports the share of cities with reported internet service provision. Column (3) reports the number of cities with new internet service provision in that year and column (4)

Table 3.5: Enforcement Data, 1996-2006

	Share of Cities Inspected	Average Number of Inspections	Average Number of Inspections Per 100 Registered Establishments in 1995	Standard Deviation of Number of Inspections Per 100 Registered Establishments in 1995
1996	0.46	82.0	11	32
1998	0.55	68.5	12	32
2000	0.62	81.5	18	44
2002	0.61	69.4	18	58
2004	0.62	64.2	20	113
2006	0.67	72.5	23	83

Source: Ministry of Labor administrative data on inspections (1996-2006).

Note: This table reports different statistics at the city level between 1996 and 2006. Column (1) reports the share of cities that have at least one labor inspection. Column (2) reports the average number of labor inspections across cities. Column (3) reports the maximum number of inspections, and column (4) reports the standard deviation of the number of inspections across all cities.

Table 5.1: Digital Technologies and Employment, by Broad Sector

Dep Variable: Log (Employment)$_{mkt}$	All	Manufacturing	Services	Construction	Wholesale and Retail Trade
PRO_{mt}*USE_{k}	-0.135***	-0.093***	-0.103***	-0.268**	-0.305***
	(0.014)	(0.030)	(0.023)	(0.118)	(0.030)
PRO_{mt}	0.050***	0.027*	0.048***	0.072	0.112***
	(0.009)	(0.016)	(0.017)	(0.051)	(0.016)
Number of Obs.	402,834	128,740	144,052	14,850	103,713
Impact of Internet in Tech-Intensive Industries	**-0.085*** **	**-0.066*** **	**-0.055*** **	**-0.196** **	**-0.193*** **
F-statistic	**122.6**	**12.8**	**31.9**	**5.0**	**124.0**
p-value	**0.000**	**0.000**	**0.000**	**0.025**	**0.000**
Sector-State-Year Dummies	YES	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES	YES

Sources: XXX.

Notes: XXX.

Table 5.2: Digital Technologies and Skills

		Non-routine Tasks	Routine Tasks	Non-routine, Cognitive Tasks
Dep Variable:	Non-Routine/ Routine Task Intensity$_{mkt}$	Cognitive/ Manual Task Intensity$_{mkt}$	Cognitive/ Manual Task Intensity$_{mkt}$	Analytical/ Interactive Task Intensity$_{mkt}$
$PRO_{mt}*USE_k$	0.045***	0.077***	0.074***	-0.011***
	(0.004)	(0.005)	(0.006)	(0.003)
PRO_{mt}	-0.023***	-0.047***	-0.037***	0.007***
	(0.002)	(0.003)	(0.003)	(0.002)
Number of Obs.	402,834	402,834	402,834	402,834
Impact of Internet in				
Tech-Intensive Industries	**0.023*** **	**0.030*** **	**0.037*** **	**-0.004** **
F-statistic	**126.7**	**116.4**	**100.2**	**4.9**
p-value	**0.000**	**0.000**	**0.000**	**0.026**
Sector-State-Year Dummies	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES

Sources: XXX.
Notes: XXX.

Table 6.1: Digital Technologies, Enforcement, and Employment, by Broad Sector

Dep Variable: Log (Employment)$_{mkt}$	All	Manufacturing	Services	Construction	Wholesale and Retail Trade
$PRO_{mt}*USE_k$	-0.133***	-0.119***	-0.144***	-0.482**	-0.228***
	(0.021)	(0.046)	(0.034)	(0.206)	(0.049)
PRO_{mt}	0.046***	0.017	0.074***	0.124*	0.086***
	(0.013)	(0.023)	(0.024)	(0.075)	(0.025)
$ENF_{mKt}*PRO_{mt}*USE_k$	0.004	-0.057*	-0.022	-0.354***	0.058***
	(0.011)	(0.031)	(0.018)	(0.137)	(0.021)
$ENF_{mKt}*PRO_{mt}$	-0.005	0.003	0.013	0.093*	-0.023**
	(0.006)	(0.015)	(0.012)	(0.049)	(0.010)
$ENF_{mKt}*USE_k$	-0.017*	0.051**	-0.010	0.169*	-0.049***
	(0.010)	(0.024)	(0.016)	(0.100)	(0.016)
ENF_{mKt}	0.038***	0.033***	0.032***	0.038	0.033***
	(0.005)	(0.011)	(0.011)	(0.039)	(0.008)
Number of Obs.	402,833	128,740	144,052	14,850	103,713
Impact of Internet in Tech-Intensive Industries					
Located in Cities at the 90th Percentile of Inspections	-0.087***	-0.094***	-0.066***	-0.431***	-0.160***
F-statistic	69.1	13.3	26.7	6.9	45.1
p-value	0.000	0.000	0.000	0.009	0.000
Located in Cities at the 10th Percentile of Inspections	-0.082***	0.029	-0.042***	0.350*	-0.272***
F-statistic	40.2	0.8	6.7	3.0	85.2
p-value	0.000	0.376	0.010	0.083	0.000
Difference in Impact of Internet in Tech-Intensive Industries					
90th Percentile - 10th Percentile of Inspections	**-0.004**	**-0.123*** **	**-0.024**	**-0.781*** **	**0.113*** **
F-statistic	**0.1**	**8.6**	**1.3**	**7.8**	**8.8**
p-value	**0.798**	**0.003**	**0.251**	**0.005**	**0.003**
Sector-State-Year Dummies	YES	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES	YES

Sources: XXX

Notes: XXX

Table 6.2: Digital Technologies, Enforcement, and Skills

Dep Variable:	Non-Routine/ Routine Task $Intensity_{mkt}$	Non-routine Tasks: Cognitive/ Manual Task $Intensity_{mkt}$	Routine Tasks: Cognitive/ Manual Task $Intensity_{mkt}$	Non-routine, Cognitive Tasks: Analytical/ Interactive Task $Intensity_{mkt}$
$PRO_{mt}*USE_k$	0.072***	0.045***	0.083***	-0.012**
	(0.005)	(0.007)	(0.009)	(0.005)
PRO_{mt}	-0.030***	-0.031***	-0.039***	0.010***
	(0.003)	(0.004)	(0.005)	(0.003)
$ENF_{mKt}*PRO_{mt}*USE_k$	0.018***	-0.025***	0.003	-0.000
	(0.003)	(0.004)	(0.005)	(0.002)
$ENF_{mKt}*PRO_{mt}$	-0.005***	0.012***	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
$ENF_{mKt}*USE_k$	-0.002	0.013***	0.009**	-0.002
	(0.002)	(0.003)	(0.004)	(0.002)
ENF_{mKt}	-0.002*	-0.007***	-0.007***	0.001
	(0.001)	(0.002)	(0.002)	(0.001)
Number of Obs.	402,833	402,833	402,833	402,833
Impact of Internet in Tech-Intensive Industries				
Located in Cities at the 90th Percentile of Inspections	0.039***	0.017***	0.043***	-0.003
F-statistic	206.9	19.3	71.7	1.8
p-value	0.000	0.000	0.000	0.178
Located in Cities at the 10th Percentile of Inspections	0.003	0.051***	0.034***	-0.005**
F-statistic	1.1	131.2	34.7	5.3
p-value	0.305	0.000	0.000	0.022
Difference in Impact of Internet in Tech-Intensive Industries				
90th Percentile - 10th Percentile of Inspections	**0.036*** **	**-0.034*** **	**0.009**	**0.003**
F-statistic	**68.9**	**34.0**	**1.2**	**0.6**
p-value	**0.000**	**0.000**	**0.271**	**0.424**
Sector-State-Year Dummies	YES	YES	YES	YES
City-Industry Fixed Effects	YES	YES	YES	YES

Sources: XXX.
Notes: XXX.