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

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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 that mainly perform these tasks. In Brazil, stringent labor market institutions exist to protect workers from such displacement; but, by increasing formal labor costs, labor market regulations also constrain firms from adjusting the workforce to perform new tasks, and fully benefiting from technology adoption. We exploit administrative and survey data, and a triple differences methodology, to show that digital technology adoption shifts labor demand toward the increased performance of non-routine activities and use of cognitive abilities. Furthermore, and in contrast with labor market policy intentions, we show that *de facto* labor 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 strict labor market policies.

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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 long run gains from a more productive and flexible economy, following technology adoption, may be accompanied, in the short term, by 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, if they are too stringent, 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 private sector jobs. We further investigate how the stringency of labor market regulations influences the incentives of firms to adjust the use of different types of tasks 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. While only 15 percent of the over 5,000 Brazilian cities had local internet service in 1999, access to digital technology has grown considerably since then. By 2006, over half of all municipalities had a local internet service provider. Meanwhile, the enforcement of labor market regulations was also quite heterogeneous across the country.[1] This paper assesses whether (and how) the rollout of the provision of internet services changed the demand for different types of skills by Brazilian businesses. In addition, we assess the extent to which *de facto* labor regulations, captured by the enforcement of labor regulations, differentially impact the decision of firms to adjust the use of different types of 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.

Our empirical strategy to estimate the effect of digital technology on the demand for tasks is based on a "triple difference", or difference-in-difference-in-differences, approach. It relies on substantial variation across three different dimensions: municipalities (comparing cities with early versus late internet access), industrial categories (comparing industries with high versus low technological intensity), and time (comparing cities before and after internet adoption). Our main assumption is that differences in trends in the main outcomes of interest, between cities that received internet early compared to cities that received internet later, are constant across industries with high and low technological intensity. We rely on the fact that industries vary in their reliance on digital technology 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 (ICT). ICT intensive industries located in cities that have early access to internet services are likely early adopters of digital technology. 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 and over time differences in internet services provision 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 labor inspections per establishment in the city and one-digit sector of activity, and analyze how the effect of digital technology on the demand for tasks 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 reliance on manual abilities and routine activities, relative to low-technology industries, thereby shifting the skill composition of industries and cities toward cognitive and non-routine tasks. Among the set of routine activities, tech-intensive industries located in cities with earlier access to the internet differentially 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 to support the less educated workforce, our results suggest that labor market regulations differentially support the use of non-routine activities and cognitive abilities.

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 in 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, Fernandes, and Viollaz (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 (2019) 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

[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 (2018) for research on industrialized countries.

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]

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, as 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 (e.g., Almeida and Carneiro, 2012). 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

[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.
[4] Almeida and Poole (2017) allow for labor market institutions in analyzing the impact of trade reform on employment levels.

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 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 tasks across distinct regulatory environments. Section 6 asks whether our main findings hold for more refined task categories. 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

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

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

[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 codified, 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.

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 papers assessing the impacts of technology depending on the employer'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. 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 technology 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. 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 labor market

We exploit an administrative data set collected by the Brazilian Labor Ministry, *Relação Anual de Informações Sociais* (RAIS), capturing labor force information across all registered (formal) establishments in the country.[7] We use data for the years 1999 through 2006, the period in which the provision of internet services had a rapid rollout across the country. An important benefit of the RAIS database is that it offers detailed information on the workers' occupations, allowing us to make a deeper assessment of which abilities are required and

[7] Our paper captures the impact of digital technology adoption on the use of skills by formal sector firms. This is arguably a more relevant sample to address our main policy question than the sample of informal firms. The latter in Brazil tend to be smaller, more intensive in the use of unskilled labor, and likely have lower digital technology adoption (see Almeida and Carneiro (2009) and World Bank (2016)).

which activities are performed by the worker. The occupational data offers information on skills that goes well beyond the skill information available in many similar datasets that rely mainly on aggregate measures of educational attainment. In addition, RAIS also includes the industry and municipality of each establishment.[8] We restrict the sample as follows. First, we exclude the public and the agricultural sectors.[9] Second, as is customary in the literature, we exclude all establishments that have fewer than five employees.

In 1999, our sample 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 2006, the formal labor force has grown significantly in our sample to cover over 22 million workers, employed in 2,350 occupations across approximately 351,000 establishments, producing in 528 industries, and located in 3,608 municipalities.

We then rely on O*NET's importance scores of different abilities and activities in U.S. occupations to characterize abilities and activities across all the Brazilian occupations. We merge our sample with information on the task content of occupations measured by the U.S. Standard Occupational Classification (SOC) in the year 2000.[10] The U.S. Department of Labor surveys workers in all occupations about the abilities required and activities performed in each occupation. For each occupation, O*NET offers "importance scores", ranging between 1 and 5, across 52 "abilities" and 41 "activities". A score of 1 means that a given attribute is "Not Important", while a score of 5 means that the attribute is "Extremely Important" to the occupation.[11] Drawing on data for the United States in the year 2000 requires the assumption

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

[9] Not only is labor adjustment in the public sector unlikely to respond to the same forces as in the private sector, but the Ministry of Labor also recognizes data quality challenges there and in the agricultural sector data.

[10] 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.

[11] 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

that the same task attributes, captured by activities and 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.

The ability and activity scores are then standardized into a numerical index, between 0 and 1. This facilitates the interpretation of O*NET's ordinal importance score ranking across occupations. Denote the importance score for task attribute *a* in a CBO occupation *o* by $S_{o,a}$. Our normalized scores scale each score by the maximum value for that score across the full set of occupations *O*, as follows:

$$S'_{o,a} = \frac{S_{o,a}}{\text{argmax}\,\{S_{1,a}, \ldots, S_{O,a}\}}.$$

Our interest is in a more aggregate grouping of the task attributes than those described in the original O*NET database. Hence, for each occupation, we aggregate all attributes into four "bundles". The two main *ability* bundles are: "manual" and "cognitive". Manual abilities are further decomposed into "precision" abilities versus "other-manual" (more strength-based) abilities. Cognitive abilities are further decomposed into "analytical" versus "communication" abilities. Table 3.1 reports how we propose to aggregate the 52 O*NET *abilities* into these four distinct bundles. We consider the following *activity* bundles: "routine" versus "non-routine" activities. Routine and non-routine activities are 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 also 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 traits.[12] We believe this strengthens the value of our approach and results.

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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".

[12] This is also true for papers relying on the older (1977) Dictionary of Occupational Titles (DOT) information. For example, Autor, Levy, and Murnane (2003) classify high scores for "set limits, tolerances, and standards" as routine-cognitive occupations and high scores for "finger dexterity" as routine-manual occupations.

A glance at the data suggest a high-quality match and sensible results for the task content of Brazilian occupations. For example, 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 dependent variables aggregate over all workers, and their respective occupations, for each of these four aggregate bundles of attributes 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 variables in our sample arises only because Brazilian employers change 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 ability intensity and the non-routine-to-routine relative activity intensity in each industry-municipality and year.

3.2. Municipal technology adoption and industrial technology intensity

Rollout of internet services The Internet was launched in Brazil in 1988, but was only made available to the public in 1995. In the beginning, internet services 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 (e.g., Telefónica, Telemar, and Brazil Telecom), the dependency on the federal government was reduced. Since then, and 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.[13] 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 whether the city has a company that provides internet services.

Table 3.3 presents basic descriptive statistics for the variable capturing the internet rollout. 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 tend to be 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. Figure 3.1 illustrates the spread of the internet across the country over time. The darker areas of the map, which are also the more urban and richer areas, obtained internet services earlier than the lighter areas on the map. The municipalities in white are those 39% of cities that remain without internet service in 2006. In unreported regressions, we find that 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. Figure 3.2, illustrates the rollout of the internet over the same period 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 upon in the empirical specification proposed in this paper.

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 the October 2003 supplement, the survey asked respondents whether they use a computer at their current job. Aggregating across all

[13] According to the International Telecommunications Union, in 2010, Brazil ranked 9th in the world with 13,266,310 fixed broadband subscriptions, or 6.8 subscriptions per each 100 residents.

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.

Information from the United States is used as a proxy for the demand for ICT among Brazilian industries; that is, how intense would be the use of technology across industries in Brazil if such technology was as widespread as in 2003 in the United States. As with the O*NET data, our use of U.S. data assumes that while the levels of technological use may be different for a given industry across the two countries, the ranking of technological intensity across industries is not different, once the two countries experience the same supply level of internet service. According to the U.S. data, "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.

Table 3.4 reports average values for the ability and activity task indices across different samples, in Panels A and B, respectively. Column (1) reports averages across all the industry-municipality cells. Columns (2) and (3) report averages for cities with and without internet provision, as of 2006, and in columns (4) and (5), we report the average conditioning on whether the industry is technologically-intensive (as defined by the median value). Four facts are worth noticing in the table. First, in column (1), the relative ability and activity task indices are always less than one, signaling Brazil's comparative advantage in more manual and routine tasks. Second, the relative importance of occupations that are more intensive in non-routine tasks has marginally increased in the Brazilian workforce over time, especially in cities with internet provision and high levels of technological intensity. Third, perhaps unsurprisingly, industries located in cities with internet access (column (2) versus column (3)) and industries with higher levels of technological intensity (columns (4) versus (5)) consistently employ higher relative shares of workers in cognitive and non-routine tasks, respectively. Fourth, these differences are increasing over time. For example, tech-intensive industries use relatively greater shares of tasks with high cognitive and non-routine contents as compared to non-tech-intensive industries and this difference is larger in 2006 than it was in 1999. Figure 3.3 provides a more complete illustration of the distribution of technological intensity across industries. The vertical lines indicate average and median values.

Our triple differences empirical strategy to identify the impact of a digital technology shock exploits variation over time, in the demand for technology, as well as the geographical roll out in the supply of technology. Hence, in columns (6) and (7) of Table 3.4, we parallel this empirical strategy, and report the average of the two task indices across cities with access to internet services and in industries with high levels of ICT intensity and across cities without internet access and in industries with low levels of technology, respectively. The average cognitive-to-manual task ratio increases by 4 percentage points between 1999 and 2006 for tech-intensive industries located in cities with internet access. Meanwhile, the same average ability task ratio decreases by 3 percentage points in non-tech-intensive industries located in cities without internet access—a differential change of 6 percentage points. Similarly, in Panel B, there is a strong relative shift toward non-routine activities, measuring around 5 percentage points, particularly for those tech-intensive employers located in municipalities with internet service provision. There is no change over time in the activity task index for cities without internet and in low technology industries.

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 the Brazilian labor regulations (*Consolidação das Leis Trabalhistas*) has more than a thousand pages. To employ a formal worker in full compliance with the labor code is very costly.[14] According to the World

[14] 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.

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 is also 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.

The Ministry of Labor is designated with enforcing compliance with labor regulations at the federal level, but there is significant heterogeneity both within the country and over time in the enforcement of the law.[15] 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 report non-compliance. 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 exploit administrative city-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 a broad industrial classification (1 digit) for the years 1998, 2000, 2004, and 2006. For our analysis, we match the enforcement data to the RAIS data by city (municipal location) and industrial classification. This information identifies industries facing varying degrees of regulatory enforcement depending on where they are located.

We proxy the degree of regulatory enforcement with the intensity of labor inspections at the city-sector-year level. Our measure of labor enforcement, designed to capture the probability of a visit by labor inspectors to employers within a city-sector-year, is the logarithm of the

[15] A comprehensive explanation of the enforcement of the labor regulation system and its importance in Brazil is given in Cardoso and Lage (2007).

number of labor inspections at the city-sector level (plus one) in a given year, per establishment in the city and broad sector based on RAIS. The number of establishments is measured in a pre-shock period (1995). 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. Because the compliance process likely takes time to influence firm decisions, we also allow for a one-year lag in our enforcement measure.

Table 3.5 presents descriptive statistics on the enforcement of labor regulations nationwide between 1998 and 2006. 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 3.4, 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 3.5 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 technology on the demand for skills is based on a triple differences, or difference-in-difference-in-differences, approach. It relies on substantial variation across three different dimensions: municipalities (comparing cities with early versus late internet adoption), industrial categories (comparing industries with high versus low ICT intensity), and time (comparing cities before and after internet adoption). Furthermore, we exploit 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 technology on the demand for skills depends on the enforcement of labor regulations.

4.1. Digital technology shock

We begin with a triple 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 technological change may affect industries differently based on their (pre-determined) reliance on information and communications technology.[16] The effect of digital technology adoption is identified using across-municipality

[16] We are not aware of any direct measures of firm-specific digital technology adoption for Brazil during our time span. However, even where such measures may exist (e.g., Chile), we argue that the municipal availability of technology is a better source of identification for the impact of digital technology on task composition.

differences in internet services provision over time for industries that differentially use information technology. The main estimating equation is as follows:

$$y_{mkt} = \beta_1(INTER_{mt} * USE\_TEC_k) + \beta_2 INTER_{mt} + \varphi_{mk} + \delta_{Kst} + \varepsilon_{mkt} \quad (1)$$

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 ability and activity 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 $INTER_{mt}$). β_1, our main coefficient of interest, reports the effect of the supply-side provision of internet services interacted with a time-invariant measure of the industry's technological-intensity (USE_TEC_k), or the demand for digital technology. In other words, β_1 reports the impact of digital technology in high-tech industries relative to low-tech industries. We argue that the arrival of new internet services affects industries differently depending on whether they require information and communications technology services. Following Acemoglu and Autor (2011), as well as much of the evidence from the developed world, we hypothesize that $\beta_1 > 0$, as employers use technology to replace routine activities and manual abilities in jobs, shifting the composition of the workforce toward non-routine and cognitive tasks.

Equation (1) includes 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 technology. Because of this, the coefficient on a separately-included industry-specific tech-intensity variable (USE_TEC_k) is unidentified, and this control variable is absorbed into the fixed effects. We also include state-sector-year dummies (δ_{Kst}) to control for the impact of other policy reforms during the period.[17] Together, these will be our base set of controls.

[17] Note that these dummies are defined across a broader aggregation level than our outcome variables for both regions and sectors. The outcome variables use municipalities as regions and the detailed, 4-digit industry codes, while the dummies use states as regions and 2-digit industry codes.

It is worth noting that the main assumption in equation (1) is weaker than the one we would pose with a simple difference-in-differences approach (say, across cities and over time). For instance, it is plausible to argue that cities that are early adopters of internet services have faster growth in the non-routine task ratio in the pre-adoption period, than cities that are late internet adopters. However, identifying the effects through a triple differences estimator, and exploiting differences within cities and across high and low ICT-intensive industries, mitigates this important concern. Figure 4.1 provides the intuition for our triple differences empirical approach, illustrating how the outcome variable evolves over time according to the industrial-level technology intensity and timing of municipal-level internet adoption. As mentioned above, we can allow the pre-internet adoption trends to be different across municipalities with early or late internet adoption; that is, the slopes of the two lines in the upper part and the slopes in the two lines in the lower part of the figure can be distinct. Our main assumption is that the difference in growth rates in the pre-adoption period is the same regardless of the industry's technological intensity; in other words, we need the distances denoted as A and B to be equal. The figure also helps to illustrate the flexibility of our identification approach, as we do not need parallelism across any two segments of the lines represented in the figure.

Nevertheless, we test for these key assumptions in the following way. Once again, our identification strategy relies on whether changes in the city-industry ability and activity task indices in tech-intensive industries relative to low-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 4.1 reports results for a cross-sectional regression relating a 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. For instance, $INTER_{m1999}$, 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 that had not adopted internet services by 2006. These dummies capture pre-trends in the skill task indices for industries with the lowest intensity of technology use (USE_TEC_k=0), located in municipalities where internet services have arrived by the indicated year.

According to the results, low technology-intensive industries located in cities with early provision of internet services (adopted in 1999) report no statistically different pre-trends than similar low technology-intensive industries located in 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 in the low technology-intensive industries to municipalities that never saw the arrival of the internet during the sample period. More importantly, as attested by the interaction coefficients, 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 also report no statistically different pre-trends in our main dependent variables. The results in Table 4.1 help to validate our empirical approach.

4.2. Effect 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:

$$
\begin{aligned}
y_{mkt} = {} & \gamma_1(ENF_{mKt-1} * INTER_{mt} * USE\_TEC_k) + \gamma_2(ENF_{mKt-1} * INTER_{mt}) \\
& + \gamma_3(ENF_{mKt-1} * USE\_TEC_k) + \gamma_4 ENF_{mKt-1} \\
& + \beta_1(INTER_{mt} * USE\_TEC_k) + \beta_2 INTER_{mt} + \varphi_{mk} + \delta_{Kst} + \varepsilon_{kmt} \qquad (2)
\end{aligned}
$$

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 labor inspections.

Our main parameter of interest is γ_1, which captures the distinct effect of internet adoption according to the level of regulatory enforcement, or the heterogeneity in β_1 across regulatory enforcement regimes. We rely on differential effects of quasi-exogenous technology shocks for industries located in diverse policy environments—a quadruple-interaction effect—following a recent trend in the program evaluation literature.

One concern relates 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 the levels of enforcement. The specification in equation (2) includes city-industry fixed effects, helping to minimize any concerns regarding the endogeneity in the level of enforcement. Our main identification is based on *changes* in the enforcement of labor market regulations over time, as in Almeida and Poole (2017).

However, one could still question the exogeneity of changes in enforcement at the city-sector level to changes in the use of certain tasks in the labor market. We note that our empirical methodology has three features to deal with this potential problem. First, in our main reduced form equation, we control for time-state-broad sector cell fixed effects (δ_{Kst}). Therefore, the relevant variation on labor inspection and potential confounders should happen within states, across municipalities. Second, we use lagged values for labor inspection to avoid simultaneous correlation. Finally, Almeida and Poole (2017) show that including changes in municipal and year characteristics correlated with enforcement do not significantly change the way enforcement affects labor market outcomes.[18]

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 interaction term (γ_1), and by considering lagged values of the main enforcement measure. Like in equation (1), we are interested in the impact of digital technology in tech-intensive industries (because tech-intensive industries located in areas with internet services provision are the likely adopters of digital technology) relative to low technology industries. In equation (2), we are also interested in how this differential effect may vary depending on the industry's regulatory environment; for example, 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.

We report the differential impact of quasi-exogenous technology shocks on labor market outcomes in different regulatory environments using: $\gamma_1(s-w)$, where s stands for strictly-enforced cities (at the 90th percentile of inspections), and w for weakly-enforced cities (at the 10th percentile of inspections). As discussed in section 2.2, if Brazilian labor policies tend to protect the least vulnerable (most skilled and experienced) workers, we expect that $\gamma_1(s-w)>0$ as industries located in strictly-enforced municipalities respond to technology shocks by differentially shifting the composition of the labor force toward skilled (non-routine and cognitive) workers. On the other hand, if labor market regulations are effective at protecting the most vulnerable (least skilled and experienced), we predict that

[18] Almeida and Poole (2017) assess how the stringency of the enforcement of labor regulations, between 1996 and 2001, affects plant size following a real exchange rate depreciation. They show that Brazilian cities with larger GDP growth experience decreases in enforcement, while population growth is a strong predictor of future enforcement growth. Developing cities, with increased access to water, electricity, and sanitation, also see decreases in enforcement, while increases in the illiteracy rate, life expectancy, the poverty rate, and years of schooling are associated with increases in enforcement. They show the robustness of their main findings on the impacts of enforcement on firm size, following an exchange rate depreciation (a difference-in-differences approach) hold regardless of the inclusion of these city-time level controls correlated with labor inspections.

$\gamma_1(s-w) < 0$, as industries shift the composition of the workforce toward routine, manual 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 tasks

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.[19] 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. As our triple differences strategy identifies the differential effect, our main parameter of interest is the impact of access to the internet for tech-intensive industries (those industries poised to adopt the new technology) relative to the impact of access to the internet for non-tech-intensive industries, the coefficient β_1.

Columns (1) and (4) report the results for the estimation of equation (1), with basic controls, including city-industry fixed effects and sector-state-year dummies for the two types of task indices. As we discuss earlier, the theoretical literature suggests that workers performing manual and routine tasks may fare worse with the introduction of new technologies, as they face more severe employment declines, because technology is complementary to other types of tasks, including cognitive and non-routine tasks. Our results confirm this routinization hypothesis for Brazil. The employment reduction in response to technical change in the use of cognitive and non-routine tasks is much less than the employment reduction of the use of

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

routine and manual tasks (see Appendix Table A.1 for dependent variables in levels). This change shifts the composition of the workforce toward more cognitive and non-routine tasks, as is evidenced by the statistically-significant and positive coefficient for the interaction term β_1 in columns (1) and (4). Those industries poised to adopt digital technology (high-tech industries) differentially increase their use of cognitive and non-routine tasks in the aftermath of a digital technology shock like internet adoption.

Robustness We test the robustness of our main findings, by estimating the specification in equation (1), including two additional sets of controls.

First, including time-varying controls for the city's level of development such as 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 two variables help to rule out the role of outsourcing in driving the changes in the demand for tasks. Together with the base set of controls, these additional time-varying, city-specific variables, account for the intermediate set of controls.[20] In columns (2) and (5) of Table 5.1, in addition to the basic set of controls reported in equation (1), we also include these city and industry time-varying controls potentially correlated with the technology shock. Accounting for these controls, the estimates show that our main coefficient of interest, β_1 remains almost unchanged. The magnitude and significance for the coefficient is almost identical to the first columns—the adoption of digital technology shifts local labor market composition toward cognitive and non-routine tasks.[21]

[20] It is worth noting that in the baseline specification, broad cross-sectional differences in city development are already captured by the city-industry fixed effects. This is important because, as discussed in section 3.2, richer and larger areas of the country likely gained access to the internet before other cities.

[21] In unreported results available by request, we find several interesting patterns in the estimates for the control variables in this specification. First, that larger and more populated cities report higher skill content of jobs (cognitive and non-routine tasks). In addition, consistent with a literature on brain versus 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

Second, we include additional controls for the rollout across cities of other technological developments, such as local television and FM radio providers (from MUNIC survey). The addition of all these variables defines our complete set of controls. Columns (3) and (6) of Table 5.1 report results of equation (1) including these 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 across the two panels.

In addition to our extended set of controls, we provide another test for the robustness of our results in Table 5.2. In this test, 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. Table 5.2 reports the results with the complete set of controls as in columns (3) and (6) in Table 5.1, confirming the main results. In fact, the magnitudes of the estimated effects are even larger.

5.2. Digital technology, labor policy enforcement, and tasks

Table 5.3 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 differential impact of the internet in tech-intensive industries (relative to low-tech industries) in strictly-enforced areas (90^{th}

results report that city-industries with high shares of exporting establishments also report higher relative cognitive and non-routine tasks.

percentile of inspections), b) the differential impact of the internet in tech-intensive industries (relative to low-tech industries) in weakly-enforced areas (10th percentile of inspections), and c) the difference in 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 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 A.2 reports 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 this 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.

Robustness As before, in addition to the complete set of controls, we test the robustness of our results by restricting the sample of cities to only those cities that had adopted internet services by 2006, abstracting from across-city differences in whether the internet exists and identifying the effect based off the timing of internet arrival. Those results are reported in Table 5.4 and confirm the main findings in Table 5.3.

Table 5.5 provides another test for the robustness of our results by labor market enforcement. Our main difference-in-differences approach asks how the demand for tasks changes in the aftermath of technology adoption differentially in technologically-intensive industries located in strongly-exposed versus weakly-exposed regulatory environments. However, in our analysis, the enforcement of labor regulations also changes over time. As we have argued previously, we rely on changes in enforcement as our main enforcement variable of interest as it is less susceptible to the endogeneity arguments that surround the level of enforcement (i.e., that enforcement is higher in highly corrupt areas, or enforcement is higher in more developed areas). Nevertheless, we provide a further test for this concern, reporting results for a more typical difference-in-differences analysis. In Table 5.5, we replace our main enforcement variable with the pre-determined, time-invariant, level of enforcement from a pre-shock (1996) year. The main results of a differential increase in cognitive and non-routine tasks in strictly-enforced cities holds. In fact, the main coefficients of interest are larger in magnitude, reflecting the endogeneity bias associated with the level of enforcement.

6. Disaggregated Tasks

We now ask whether our main findings, reported in Tables 5.1 and 5.3, 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 6.1 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 interaction coefficient. Column (1) of Table 6.2 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 relative 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 substitution 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 6.1. 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 6.2 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 6.1, 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 cognitively-oriented, non-routine tasks. Technology differentially increases the share of cognitive-non-routine tasks over manual-non-routine tasks in tech-intensive industries relative to industries with lower technological intensity. The results in Table 6.2, however, suggest that the relative shift toward cognitive versus manual non-routine tasks occurs in both strictly- and weakly-enforced cities—there is little statistical evidence that technology impacts the cognitively-oriented share of non-routine tasks differently depending on labor market regulatory enforcement.

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 6.1, 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 6.2) 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 relative to low-technology industries.

7. Conclusions and Policy Implications

There is a strong concern around the globe that technology is increasingly replacing routine, manual tasks, and potentially displacing lower educated 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 technology 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 tasks 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 shift toward the use of cognitive abilities and non-routine activities in the local labor markets. In contrast with labor policy intentions, our evidence points to the idea that labor market regulations differentially benefit the skilled workforce leading to more sophisticated abilities and activities, particularly those workers employed in non-routine, cognitive tasks.

Our work offers new insights for the design of effective education, skills, and labor policies to support the future Brazilian workforce. In an economy with progressively higher levels of technology adoption, and with increased automation, restrictive labor codes can hurt the poorest and less skilled workers hardest. The findings also pose significant implications for education policies as it highlights the urgency of preparing youth for the jobs of tomorrow that will demand new, more sophisticated skills. The paper shows that more ICT-intensive industries increasingly rely on cognitive abilities and non-routine activities in which communication and interpersonal skills are in particularly high demand. Without these twenty-first century skills, Brazilian workers will simply find it much harder to find employment in the future, and the country is likely to miss the necessary condition to fully benefit from the higher productivity and welfare gains associated with digital technology adoption.

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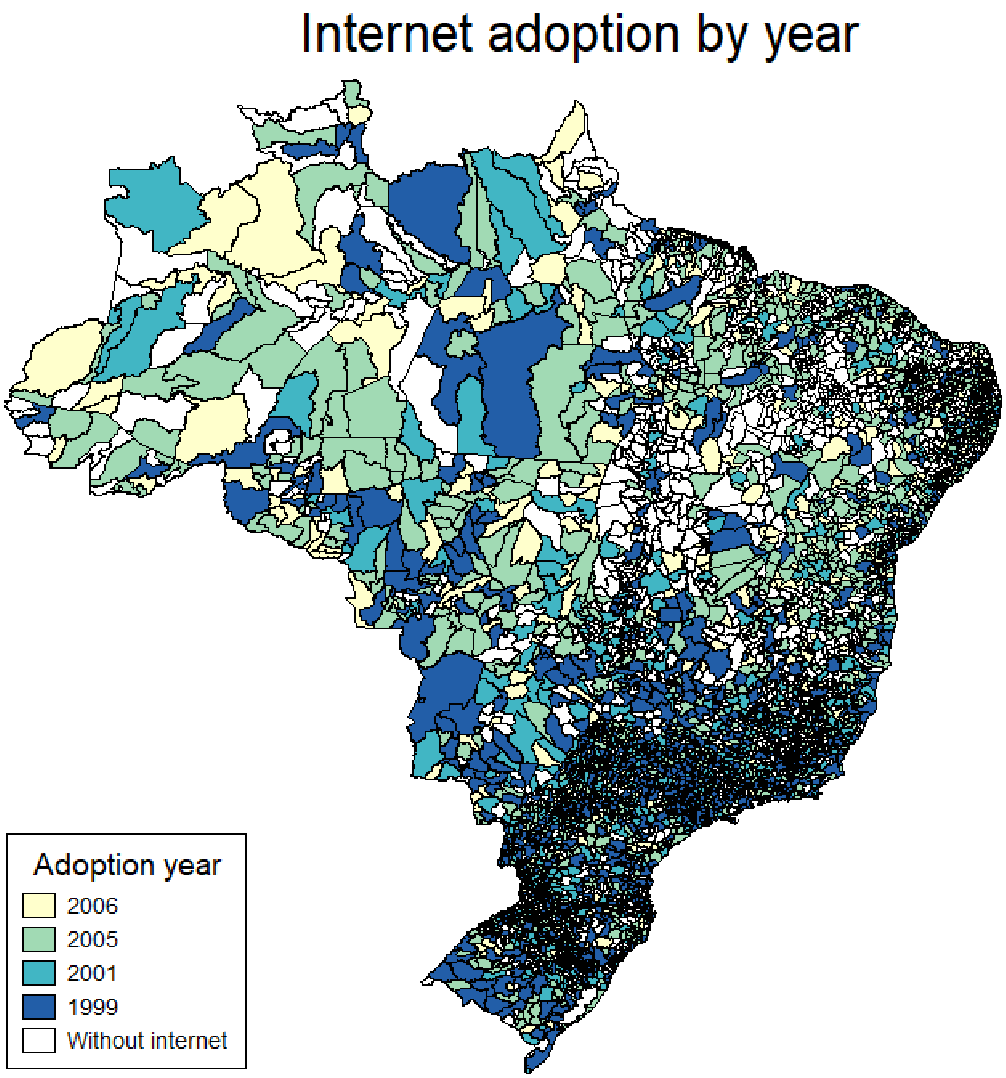
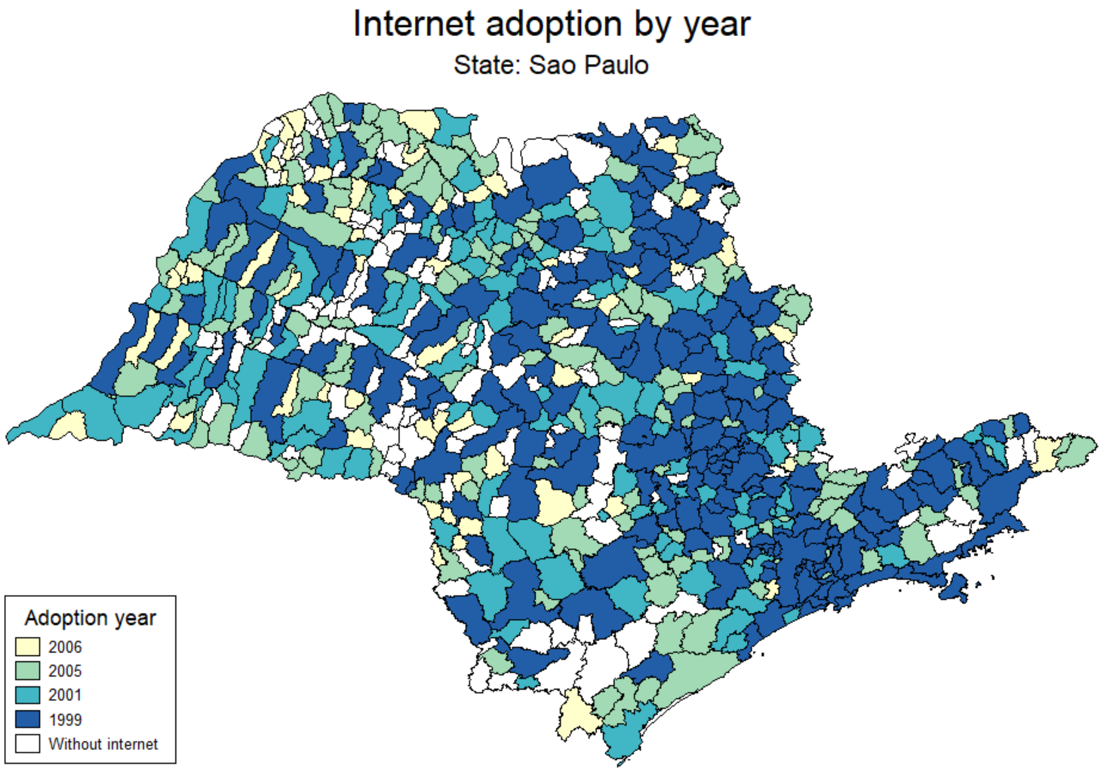
Figure 3.1: Internet Service Provision, by Municipality



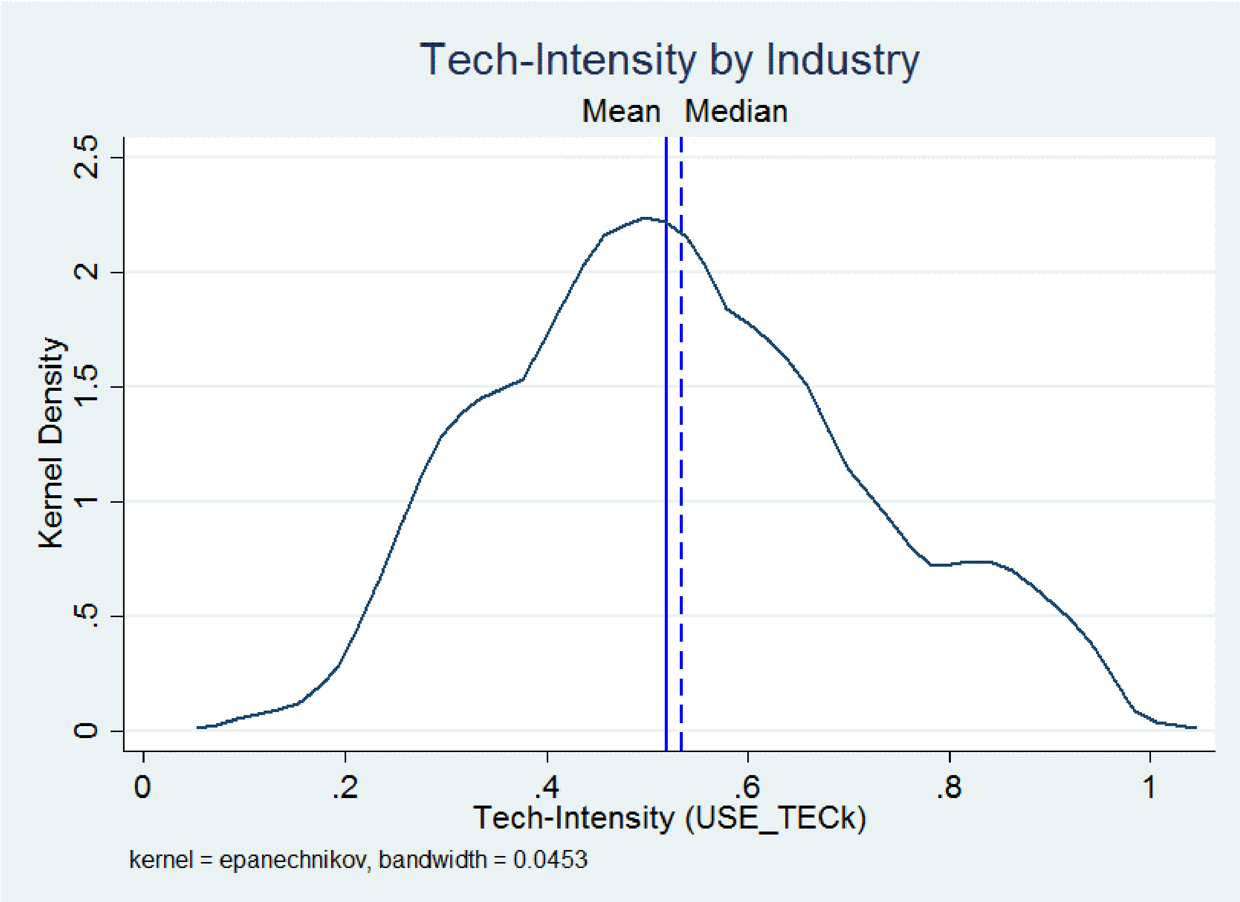
Source: IBGE.

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



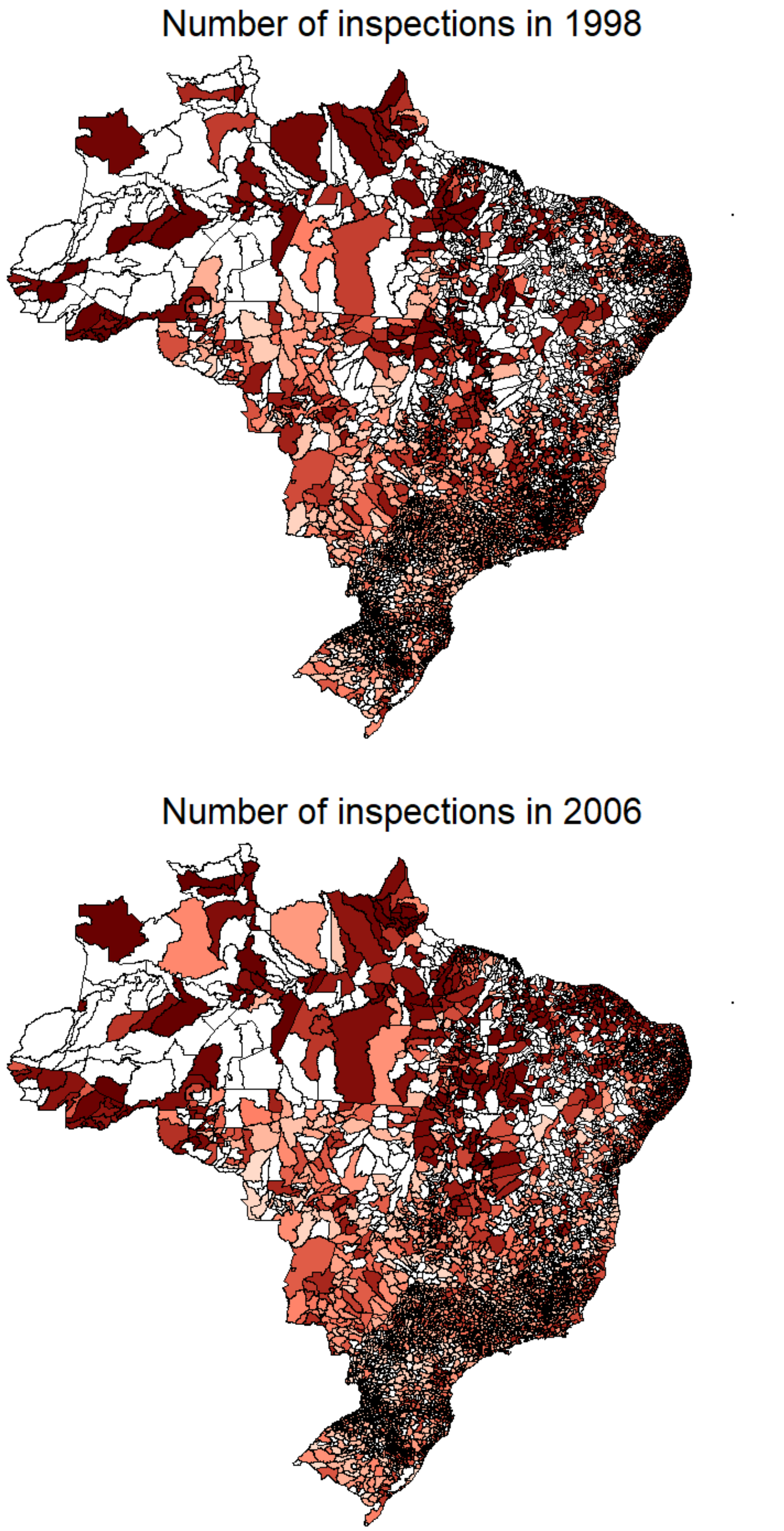
Source: IBGE.

Figure 3.3: Distribution of Technological Intensity Across Industries



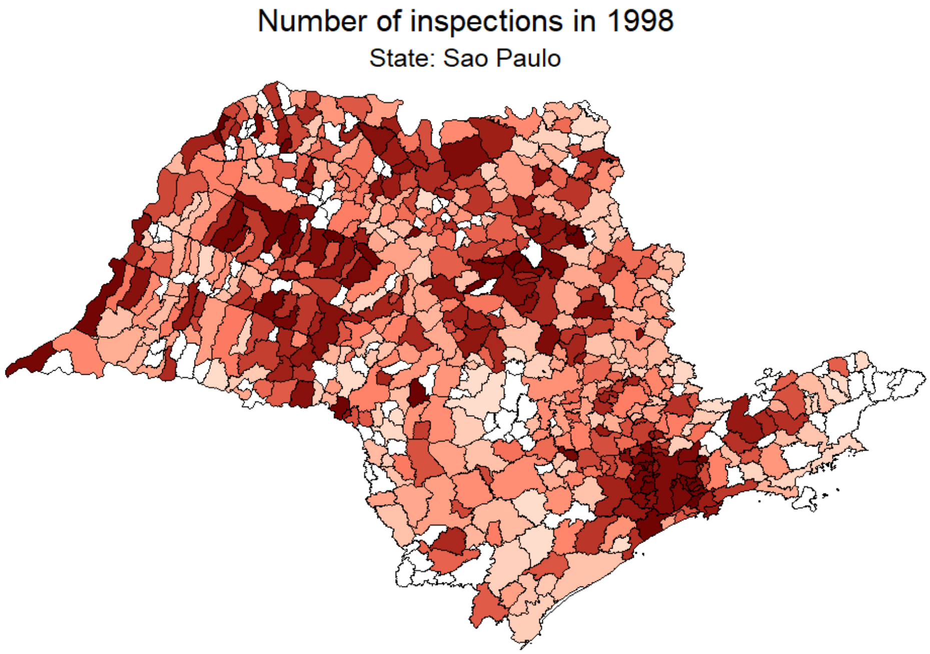
Source: RAIS; CPS.

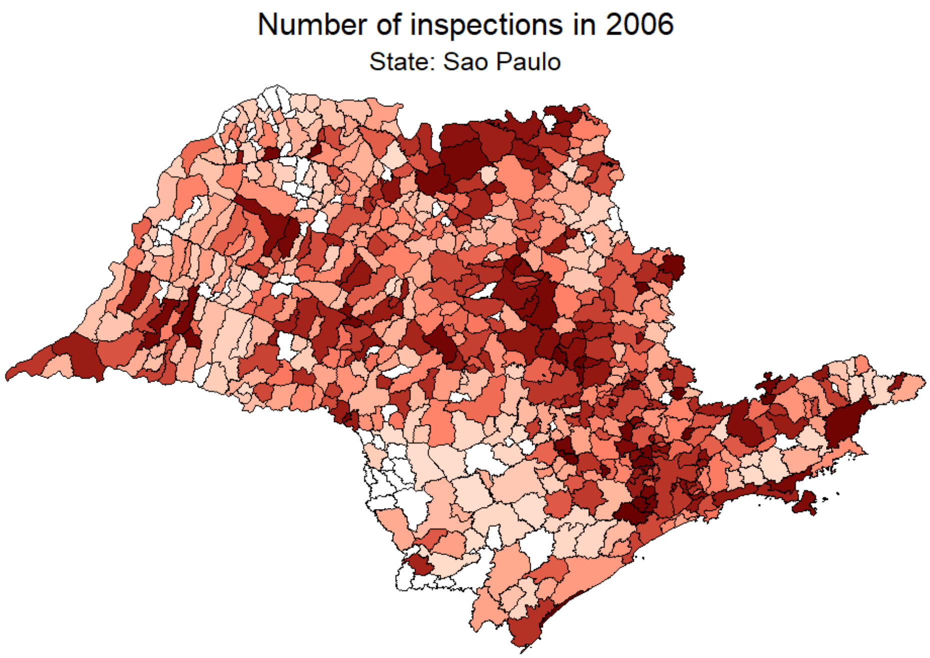
Figure 3.4: Labor Market Enforcement Intensity, by Municipality



Source: Ministry of Labor.

Figure 3.5: Labor Market Enforcement Intensity, by Municipality, São Paulo State





Source: Ministry of Labor.

Figure 4.1: Intuition of Triple Differences Approach

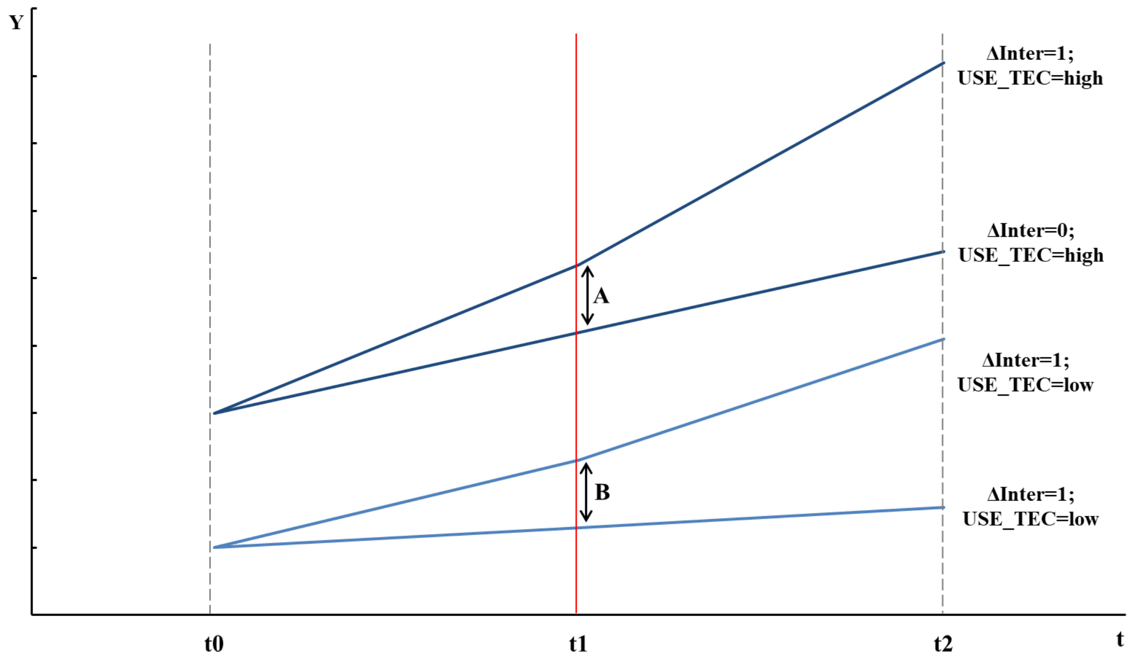


Table 3.1: O*NET Abilities Classification

Manual Abilities		Cognitive Abilities	
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 Activities		Non-Routine Activities	
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: 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.

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 3.4: 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 (4) and (5) 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 3.5: 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; RAIS.

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 4.1: 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)
USE_TEC$_k$	0.000	0.004
	(0.014)	(0.013)
INTER$_{m1999}$	-0.004	0.006
	(0.008)	(0.008)
INTER$_{m2001}$	-0.005	0.001
	(0.009)	(0.008)
INTER$_{m2005}$	-0.001	-0.002
	(0.009)	(0.008)
INTER$_{m2006}$	-0.006	-0.004
	(0.013)	(0.011)
INTER$_{m1999}$*USE_TEC$_k$	0.010	-0.012
	(0.014)	(0.013)
INTER$_{m2001}$*USE_TEC$_k$	0.015	0.001
	(0.015)	(0.012)
INTER$_{m2005}$*USE_TEC$_k$	0.004	0.005
	(0.015)	(0.013)
INtER$_{m2006}$*USE_TEC$_k$	0.017	0.015
	(0.023)	(0.021)
Sector-State Dummies	YES	YES
Observations	64,184	64,184

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. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

Table 5.1: The Effect of Digital Technology on Tasks

Dep. Variable:	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)
$INTER_{mt}$*USE_TEC_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)
$INTER_{mt}$	-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
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 (4) report the baseline specification, as reported in equation (1) in the text. Columns (2) and (5) 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. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

Table 5.2: Robustness, Cities with Internet by 2006

Dep. Variable:	Log (Cognitive/ Manual Tasks)$_{mkt}$ (1)	Log (Non-Routine/ Routine Tasks)$_{mkt}$ (2)
$INTER_{mt}$*USE_TEC_k	0.038***	0.072***
	(0.007)	(0.007)
$INTER_{mt}$	-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
Observations	312,090	312,090

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

Notes: Columns (1) and (2) 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 and the non-routine-to-routine task ratio, respectively, with the complete set of controls. Robust standard errors are clustered at the city-industry level. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

Table 5.3: The Effect of Digital Technology on Tasks, by Labor Market Enforcement

Dep. Variable:	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)
$INTER_{mt}$*USE_TEC_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)
$INTER_{mt}$	-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}*$INTER_{mt}$*USE_TEC_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}*$INTER_{mt}$	-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_TEC_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
Differential Impact of Internet in Tech-Intensive Industries						
Located in Cities at the 90th Percentile of Inspections	0.057***	0.062***	0.056***	0.105***	0.108***	0.094***
F-statistic	32.5	39.3	30.2	129.5	137.0	101.0
Located in Cities at the 10th Percentile of Inspections	0.018	0.019	0.008	0.034***	0.034***	0.029***
F-statistic	2.2	2.4	0.4	9.5	9.5	6.8
Difference in Differential Impact of Internet in Tech-Intensive Industries						
90th Percentile - 10th Percentile of Inspections	0.038**	0.043***	0.048***	0.071***	0.074***	0.065***
F-statistic	5.4	6.9	7.8	23.5	25.6	18.1
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 (4) report the baseline specification, as reported in equation (2) in the text. Columns (2) and (5) 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, along with their enforcement interactions. Robust standard errors are clustered at the city-industry level. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level. We also report: a) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strictly-enforced areas (90th percentile of inspections), b) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in weakly-enforced areas (10th percentile of inspections), and c) the difference in the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strict versus weak enforcement environments (the difference between (a) and (b)). The corresponding F-statistics are for the null hypothesis that the sum of the coefficients is significantly different from zero.

Table 5.4: Robustness, Cities with Internet by 2006

Dep. Variable:	Log (Cognitive/ Manual Tasks)$_{mkt}$ (1)	Log (Non-Routine/ Routine Tasks)$_{mkt}$ (2)
$INTER_{mt}$*USE_TEC_{k}	0.076***	0.114***
	(0.012)	(0.011)
$INTER_{mt}$	-0.043***	-0.055***
	(0.007)	(0.006)
ENF_{mKt-1}*$INTER_{mt}$*USE_TEC_{k}	0.026***	0.031***
	(0.007)	(0.006)
ENF_{mKt-1}*$INTER_{mt}$	-0.014***	-0.014***
	(0.004)	(0.003)
ENF_{mKt-1}*USE_TEC_{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
Differential Impact of Internet in Tech-Intensive Industries		
Located in Cities at the 90th Percentile of Inspections	0.069***	0.106***
F-statistic	42.1	117.1
Located in Cities at the 10th Percentile of Inspections	-0.003	0.022*
F-statistic	0.1	3.3
Difference in Differential Impact of Internet in Tech-Intensive Industries		
90th Percentile - 10th Percentile of Inspections	0.072***	0.084***
F-statistic	14.9	25.3
Observations	312,090	312,090

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

Notes: Columns (1) and (2) 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 and the city-sector-year average non-routine-to-routine task ratio, with the complete sets of controls. Robust standard errors are clustered at the city-industry level. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level. We also report: a) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strictly-enforced areas (90th percentile of inspections), b) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in weakly-enforced areas (10th percentile of inspections), and c) the difference in the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strict versus weak enforcement environments (the difference between (a) and (b)). The corresponding F-statistics are for the null hypothesis that the sum of the coefficients is significantly different from zero.

Table 5.5: Robustness, Time-Invariant Labor Market Enforcement

Dep. Variable:	Log (Cognitive/ Manual Tasks)$_{mkt}$ (1)	Log (Non-Routine/ Routine Tasks)$_{mkt}$ (2)
$INTER_{mt}$*USE_TEC_k	0.073***	0.108***
	(0.013)	(0.012)
$INTER_{mt}$	-0.042***	-0.052***
	(0.007)	(0.007)
ENF_{mK1996}*$INTER_{mt}$*USE_TEC_k	0.022***	0.023***
	(0.007)	(0.007)
ENF_{mK1996}*$INTER_{mt}$	-0.012***	-0.010***
	(0.004)	(0.004)
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
Differential Impact of Internet in Tech-Intensive Industries		
Located in Cities at the 90th Percentile of Inspections	0.067***	0.102***
F-statistic	36.2	89.4
Located in Cities at the 10th Percentile of Inspections	0.002	0.034**
F-statistic	0.0	6.0
Difference in Differential Impact of Internet in Tech-Intensive Industries		
90th Percentile - 10th Percentile of Inspections	0.065***	0.067***
F-statistic	8.9	11.1
Observations	336,115	336,115

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

Notes: Columns (1) and (2) 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 and the city-sector-year average non-routine-to-routine task ratio, with the complete sets of controls and a time-invariant, pre-period enforcement variable. Robust standard errors are clustered at the city-industry level. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level. We also report: a) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strictly-enforced areas (90th percentile of inspections), b) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in weakly-enforced areas (10th percentile of inspections), and c) the difference in the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strict versus weak enforcement environments (the difference between (a) and (b)). The corresponding F-statistics are for the null hypothesis that the sum of the coefficients is significantly different from zero.

Table 6.1: The Effect of Digital Technology on the Use of Specific Tasks

	Cognitive Tasks	Manual Tasks	Non-Routine Tasks	Routine Tasks
Dep. Variable:	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)
$INTER_{mt}$*USE_TEC_k	-0.045***	-0.048***	0.034***	0.046***
	(0.006)	(0.005)	(0.009)	(0.011)
$INTER_{mt}$	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
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) 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-manual 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). *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

Table 6.2: The Effect of Digital Technology on the Use of Specific Tasks, by Labor Market Enforcement

	Cognitive Tasks	Manual Tasks	Non-Routine Tasks	Routine Tasks
Dep. Variable:	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)
$INTER_{mt}$*USE_TEC_k	-0.070***	-0.072***	0.034**	0.064***
	(0.010)	(0.008)	(0.013)	(0.017)
$INTER_{mt}$	0.036***	0.023***	-0.031***	-0.042***
	(0.006)	(0.003)	(0.007)	(0.010)
ENF_{mKt-1}*$INTER_{mt}$*USE_TEC_k	-0.018***	-0.019***	-0.001	0.013
	(0.005)	(0.004)	(0.007)	(0.009)
ENF_{mKt-1}*$INTER_{mt}$	0.011***	0.008***	-0.002	-0.010**
	(0.003)	(0.002)	(0.004)	(0.005)
ENF_{mKt-1}*USE_TEC_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
Differential Impact of Internet in Tech-Intensive Industries				
Located in Cities at the 90th Percentile of Inspections	-0.070***	-0.072***	0.034***	0.064***
F-statistic	50.9	91.4	8.2	15.8
Located in Cities at the 10th Percentile of Inspections	-0.011	-0.010*	0.038***	0.023
F-statistic	2.4	3.8	7.2	2.3
Difference in Differential Impact of Internet in Tech-Intensive Industries				
90th Percentile - 10th Percentile of Inspections	-0.059***	-0.063***	-0.004	0.041
F-statistic	11.9	25.8	0.0	1.9
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 (1) 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-manual 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 5.3, columns (3) and (6). *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level. We also report: a) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strictly-enforced areas (90th percentile of inspections), b) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in weakly-enforced areas (10th percentile of inspections), and c) the difference in the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strict versus weak enforcement environments (the difference between (a) and (b)). The corresponding F-statistics are for the null hypothesis that the sum of the coefficients is significantly different from zero.

Appendix Table A.1: The Effect of Digital Technology on Tasks (Levels)

Dep. Variable:	Log (Cognitive Tasks)$_{mkt}$ (1)	Log (Manual Tasks)$_{mkt}$ (2)	Log (Non-Routine Tasks)$_{mkt}$ (3)	Log (Routine Tasks)$_{mkt}$ (4)
$INTER_{mt}$*USE_TEC_k	-0.145***	-0.180***	-0.113***	-0.181***
	(0.013)	(0.013)	(0.013)	(0.013)
$INTER_{mt}$	0.092***	0.114***	0.082***	0.117***
	(0.008)	(0.008)	(0.008)	(0.008)
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
Observations	336,115	336,115	336,115	336,115

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

Notes: Columns (1) through (4) show the estimates of equation (1) using ordinary least squares, when the dependent variable is the city-sector-year average level of cognitive tasks, manual tasks, non-routine tasks, and routine tasks, respectively, with the complete set of controls. Robust standard errors are clustered at the city-industry level. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level.

Appendix Table A.2: The Effect of Digital Technology on Tasks (Levels), by Labor Market Enforcement

Dep. Variable:	Log (Cognitive Tasks)$_{mkt}$ (1)	Log (Manual Tasks)$_{mkt}$ (2)	Log (Non-Routine Tasks)$_{mkt}$ (3)	Log (Routine Tasks)$_{mkt}$ (4)
$INTER_{mt}$*USE_TEC_k	-0.087***	-0.147***	-0.056***	-0.156***
	(0.019)	(0.019)	(0.018)	(0.018)
$INTER_{mt}$	0.060***	0.097***	0.053***	0.103***
	(0.011)	(0.011)	(0.011)	(0.011)
ENF_{mKt-1}*$INTER_{mt}$*USE_TEC_k	0.041***	0.023**	0.042***	0.018*
	(0.011)	(0.011)	(0.011)	(0.010)
ENF_{mKt-1}*$INTER_{mt}$	-0.022***	-0.012*	-0.020***	-0.009
	(0.006)	(0.006)	(0.006)	(0.006)
ENF_{mKt-1}*USE_TEC_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)
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
Differential Impact of Internet in Tech-Intensive Industries				
Located in Cities at the 90th Percentile of Inspections	-0.098***	-0.153***	-0.066***	-0.160***
F-statistic	34.3	76.9	16.0	92.8
Located in Cities at the 10th Percentile of Inspections	-0.208***	-0.216***	-0.179***	-0.208***
F-statistic	91.2	92.6	67.8	98.4
Difference in Differential Impact of Internet in Tech-Intensive Industries				
90th Percentile - 10th Percentile of Inspections	0.110***	0.063**	0.113***	0.048*
F-statistic	14.8	4.5	15.6	3.0
Observations	336,115	336,115	336,115	336,115

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

Notes: Columns (1) through (4) show the estimates of equation (2) using ordinary least squares, when the dependent variable is the city-sector-year average level of cognitive tasks, manual tasks, non-routine tasks, and routine tasks, respectively, with the complete set of controls. Robust standard errors are clustered at the city-industry level. *** denotes significance at the 1 percent level; ** denotes significance at the 5 percent level; * denotes significance at the 10 percent level. We also report: a) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strictly-enforced areas (90th percentile of inspections), b) the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in weakly-enforced areas (10th percentile of inspections), and c) the difference in the differential impact of the internet in tech-intensive industries, relative to non-tech-intensive industries, in strict versus weak enforcement environments (the difference between (a) and (b)). The corresponding F-statistics are for the null hypothesis that the sum of the coefficients is significantly different from zero.