The Wage and Inequality Impacts of Broadband Internet

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December 31, 2021

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Abstract

Who benefits from the adoption of communication technology in the workplace? I combine worker-level wage data with information on broadband adoption by Brazilian firms to estimate the effects of broadband on wages and inequality. Overall, wages increase 2.2 percent following broadband adoption. Consistent with theories of biased technical change, wages increase the most for workers engaged in non-routine cognitive tasks and occupations that require using computer technology. Additionally, I estimate the effect of broadband on selected quantiles of the within-firm wage distribution to test predictions from theories of "management by exception" about the effects of communication technology on different levels of the organizational hierarchy. Consistent with theory, I find that upper-level employees benefit more than employees at lower levels. Furthermore, wage inequality among managers increases following broadband adoption, while inequality among workers decreases or is unchanged. Both new hires and firms' existing employees benefit from broadband adoption, which indicates that broadband's effects are not driven only by better recruitment of new employees.
JEL Codes: J24, J31, O33

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I am grateful to Shane Greenstein, Michael Luca, Raffaella Sadun, and Deepak Malhotra for their advice and guidance. I thank Aguinaldo Nogueira Maciente for graciously sharing his excellent crosswalk for Brazilian and U.S. occupation codes. I also thank the *HBS Latin America Research Center*, *Partners of the Americas*, *Harvard Business School*, and the *Harvard Economics Department* for financial and logistical support of this project.

1 Introduction

Broadband, and the internet more generally, are among the most important technologies of the past several decades. Nearly 60 percent of people worldwide now access the internet, and its transformation from a technology used by fewer than 1 percent of people in the mid-1990s to the ubiquitous network of today has potentially large effects on firm organization and wages. Computers and the internet are among the most widely cited sources of recent skill-biased and routine-biased technical change (Card and DiNardo 2002), and many scholars have highlighted the special importance of network technologies and suggested their much greater role in explaining increasing wage inequality than the use of computers for individualized tasks such as word processing (Bresnahan 1999, Card and DiNardo 2002, Bresnahan et al. 2002).

Unfortunately, the internet, and especially modern communication technologies like broadband, have been subjected to much less empirical scrutiny than computers. Studies mostly examine the average effects of broadband using aggregate or cross-sectional data, rather than the distributional effects using micro-level data on workers and the technology adopted inside their firms. The latter are important, however, for testing several theoretical predictions about the effects of technology on wage inequality and for informing public policies aimed at closing the "digital divide." A large literature on skill-biased technical change (SBTC) highlights the potential for digital technologies to substitute for low-skill workers performing routine tasks, while complementing high-skill workers in non-routine tasks (Katz and Autor 1999, Autor et al. 2003, Acemoglu 2002, Acemoglu and Autor 2011). Thus, workers are unlikely to benefit equally from new technologies. While the insights of this literature are extremely helpful for guiding policy, few studies specifically examine broadband.

Many studies treat information and communication technology (ICT) as a homogeneous capital stock, but extrapolating the results from studies of information technology or ICT generally to the case of broadband may be inappropriate. The theory of "management by exception" suggests that information technology (IT) and communication technology (CT) have distinct effects on firm organization and wage inequality (Garicano and Rossi-Hansberg 2006, Bloom et al. 2014). IT reduces the cost of storing and processing data, allowing organizations to automate business functions and empower workers by decentralizing decision-making. CT, however, reduces the cost of communication within and between organizations, allowing managers to more easily share knowledge with subordinates, access information outside their organizations, and centralize decision-making. These effects of CT are predicted to increase wage inequality between levels of the organizational hierarchy (e.g., between managers and workers) and increase (decrease) inequality among managers (workers). Research has examined this theory's predictions about worker autonomy and centralization (Bloom et al. 2014), but scholars have not empirically tested the theory's novel predictions about the effects of CT on the wage distribution between and within levels of the organizational hierarchy.

I combine employer-employee matched data from Brazil with longitudinal, firm-level data on broadband adoption to test predictions about the effects of communication technology on wages and inequality within firms. I find that wages increase an average of 2.2 percent following firm broadband adoption, but the effect of broadband is heterogeneous. Wages increase the most for workers in occupations that require the use of information technology, and regressions of wages on the task profile of jobs show broadband most benefits employees performing non-routine, cognitive tasks and least benefits workers performing routine, cognitive tasks. Intuitively, wage rates for both non-routine and routine manual tasks are unaffected by broadband.

Consistent with theories of "management by exception," I find that wages increase more for managers than workers following broadband adoption. Analyses of the entire within-firm wage distribution suggest that (a) within-firm wage inequality increases, and (b) wage inequality increases within higher levels of the organizational hierarchy (e.g., between managers) but not within lower levels (e.g., between workers). These findings support predictions regarding the effects of communication technology on wage inequality (Garicano and Rossi-Hansberg 2006), and to my knowledge provide the first direct evidence connecting adoption and use of advanced communication technology to widening pay gaps within organizations.

This study contributes to the literature on the economic impact of broadband, internet connectivity, and biased technical change in several ways. First, I offer a novel test of predictions from theories of "management by exception." Prior research has studied the average effects of broadband on wages (Kolko 2012, Forman et al. 2012, Ivus and Boland 2015) and emphasized the effects on workers of different skill levels or the returns to different tasks (Atasoy 2013, Akerman et al. 2015, Almeida et al. 2017, Dutz et al. 2017). Research has not, however, examined the returns to communication technology at different levels of the organizational hierarchy.

Second, this study is among the first to combine within-firm variation on technology use with large-sample microdata on the wages, occupation, and characteristics of individual workers. Research on how the internet affects workers in Brazil (Almeida et al. 2017, Dutz et al. 2017), Africa (Hjort and Poulsen 2019), Norway (Akerman et al. 2015), Canada (Ivus and Boland 2015), the United States (Gillett et al. 2006, Forman et al. 2012, Kolko 2012, Atasoy 2013), and other developed countries (Carthy and Lyons 2019, Stockinger 2019) instead relies on geographic variation in internet availability and/or cross-sectional variation in firm adoption. I build on these studies by observing the same firm and workers before and after the adoption of broadband, which is valuable for assessing whether technology adoption changes wages or is merely associated with higher wages because higher wage workers are more likely to use technology (DiNardo and Pischke 1997).

Third, my results contribute to a nascent literature on ICT in developing countries (Hjort and Tian 2021). The context of this study, Brazil, is novel because most prior studies of broadband, and SBTC generally, focus on developed countries. Whether estimates of broadband's effects in developed countries apply to developing, middle-income countries like Brazil is a priori unclear. Acemoglu and Zilibotti (2001) explain how developed countries create technologies that complement the abundance of skilled workers and that such technologies may be of less use in countries with a relative lack of skills. They show that the adoption of ICT in developing countries can lead to a technology-skill mismatch that prevents firms and workers from realizing the benefits of new technology. Studies of broadband and skill premia in developing countries may thus come to different conclusions than those focused on developed countries in Europe and North America. Furthermore, the implications of biased technical change for inequality may be of particular interest in developing countries that already have extreme inequality and are pursuing policies to mitigate it.

Finally, the findings of this study have practical importance. Dozens of countries have adopted national broadband plans, and both developed and developing countries are making public investments in broadband infrastructure. In the United States, for example, the Infrastructure Investment and Jobs Act (2021) allocates \$65b to broadband infrastructure. Policymakers hope that these investments will spur economic and wage growth while also closing the "digital divide," defined as demographic, geographic, and socioeconomic disparities in access to information and communication technology (Kruger and Gilroy 2019). There is little scientific evidence, however, to support these claims, especially in developing countries. Several studies suggest broadband expansion is beneficial for macroeconomic growth (Koutroumpis 2009, Czernich et al. 2011), but empirical research also indicates the gains are geographically concentrated (Forman et al. 2012) and that the benefits of public investments are often overestimated (Greenstein and McDevitt 2011). Furthermore, the evidence is especially limited regarding the distributional, worker-level effects of broadband. Studies like this one can help clarify the extent to which wage gains from broadband are widely shared, which is relevant for both shaping policy and decisions about how to finance public expenditures.

2 Theoretical Framework and Hypotheses

Several theories speak to the likely effects of broadband technology on wage inequality. Among these, the most prominent are "Ricardian" task-based models and models of "management of exception" or knowledge-based hierarchies (Acemoglu 2002, Acemoglu and Autor 2011, Autor et al. 2003, Garicano 2000, Garicano and Rossi-Hansberg 2015).

Task-based models have been the most widely used in empirical research and emphasize the ability of technology to substitute for or complement workers who differ in skill and the tasks they perform. This affects labor demand and therefore wages (Acemoglu and Autor 2011). Theories of "management by exception" similarly allow technology to benefit certain workers while potentially substituting for the labor of others, although the mechanisms are different (Garicano and Rossi-Hansberg 2015). These models treat production as a process of solving problems and endogenize the creation of organizational hierarchies in which employees at higher levels solve harder or more unusual problems and earn more as a result (Garicano 2000). IT and CT have distinct effects, with IT affecting the cost of learning how to solve problems and CT affecting the cost of passing problems up the hierarchy to more knowledgeable employees. This in turn affects the optimal hierarchy and amount of knowledge to acquire, and leads to several predictions about wages. Some of these predictions overlap with those of task-based models, and both are useful for assessing the likely impact of broadband on wage inequality. Models of "management by exception," however, also make several unique predictions about the effect of communication technologies like broadband on wages and inequality within and across different levels of the organizational hierarchy. These have received little, if any, empirical attention.

2.1 Task-Based Models

In task-based models, production consists of performing a set of tasks. Workers are substitutes in performing tasks, but differ in their skill level and productivity (Acemoglu and Autor 2011). More skilled workers have a comparative advantage in more complicated tasks, such as non-routine knowledge work, and technology alters the relative productivity of different skill types or directly substitutes for workers in performing certain tasks. For example, computers are thought to have contributed to the automation of routine tasks typically performed by middle-skill workers and thus reduced demand for their labor and lowered wages (Autor et al. 2003). Task-based models also predict that the wages of high-skill (low-skill) workers will increase (decrease) in response to biased technologies that increase the productivity of high-skill workers (Acemoglu and Autor 2011).[1]

Research on broadband adoption in developed countries suggests it is skill-biased towards high-skill workers (Akerman et al. 2015), and as I explain in Section 3, broadband is likely to substitute for workers in at least some routine tasks while complementing workers who perform non-routine tasks and use computers. The task-based approach to studying technical change therefore predicts:

Hypothesis 1 *The wages of workers performing non-routine cognitive tasks will increase more than the wages of workers performing routine cognitive tasks following broadband adoption.*

Hypothesis 2 *The wages of workers whose jobs involve the use of ICT will increase more than the wages of other workers following broadband adoption.*

[1] The precise predictions depend on the assumed structure of tasks, but task-based models are generally offered as an explanation for the declining or stagnant real wages of less-skilled workers, increasing wages among skilled workers, and the rising inequality of the past several decades.

2.2 Management by Exception

The task-based approach is widely used and extremely useful for thinking about the effects of ICT on wages. Theories of "management by exception," however, generate several unique predictions about the effects of communication technologies on wages that are absent from the task-based model and have not been tested empirically (Garicano and Rossi-Hansberg 2006, Bloom et al. 2014, Garicano and Rossi-Hansberg 2015).

In these models, production occurs by matching problems that differ in their frequency or difficulty with solutions (Garicano 2000, Garicano and Rossi-Hansberg 2006). Employees with more information/knowledge can solve more problems, but acquiring information is costly, especially for less-skilled workers. Therefore, as an alternative to acquiring information, a worker who does not know how to solve a problem can ask someone with more information for help, which results in a communication cost. Garicano (2000) and Garicano and Rossi-Hansberg (2006) show how hierarchies allow organizations to economize on information acquisition and communication costs by assigning workers to learn and solve the most common problems while passing more unusual problems to managers. Under this structure, managers incur greater costs of acquiring information about unusual problems, but can then use this information intensively by helping several workers solve their most difficult problems. Hence the phrase "management by exception:" workers deal with common, well-understood problems but give difficult problems (the exceptions) to managers.

These models suggest that improvements in information technology that reduce the cost of acquiring, storing, and analyzing information lead to decentralization; workers at all levels of a firm acquire more knowledge and the responsibility for solving more problems moves down the organizational hierarchy. This makes skill differentials between workers more important and increases inequality at all levels of the organization (Garicano and

Rossi-Hansberg 2006).[2]

Communication technologies like broadband, however, reduce the cost of passing problems up the hierarchy so that managers can assist workers. This leads to greater centralization and a greater reliance on employees higher in the organization to acquire knowledge and solve problems. Wage inequality thus increases at the top of the hierarchy (e.g., among managers) but decreases at the bottom of the hierarchy (e.g., among production workers) because differences in the skill of production workers become less important when they handle fewer problems. Furthermore, the wage gap between hierarchical layers (e.g., managers and workers) increases as knowledge at the bottom of the hierarchy becomes less important for production.[3]

Bloom et al. (2014) corroborate several of this model's predictions in a cross-sectional analysis of technology use and employee autonomy in a large sample of U.S. and European firms. Due to data limitations, however, they do not observe changes in technology use over time or examine wages. In this paper, I lack measures of worker autonomy, but have rich longitudinal data on wages, worker characteristics, and the use of broadband. I therefore focus on the following, previously untested predictions regarding communication technology:

Hypothesis 3 *The wages of managers will increase more than the wages of other employees following broadband adoption.*

Hypothesis 4 *Wage inequality among managers (workers) will increase (decrease) following broadband adoption.*

[2] Skill differentials become more important because knowledge acquisition is cheaper for higher-ability workers. When workers are expected to solve more problems by acquiring knowledge, their level of skill becomes more important.

[3] A key benefit of knowledgeable workers is economizing on communication costs. When workers can solve a problem, the firm avoids the cost of bothering a manager. This becomes less important, however, as communication costs decline, which makes paying for knowledgeable workers less attractive.

3 Broadband Technology

Although several papers suggest broadband complements workers in performing non-routine tasks, while substituting for routine tasks, few are specific about how high-speed internet access might do this. To provide evidence, and illustrate some differences between CT and IT, I examine the results of a government survey of Brazilian firms and offer several anecdotal examples of firms using broadband gleaned from interviews with managers in Brazil.

Table 1 shows results from a survey of Brazilian firms that asked about internet use.[4] The table shows results for manufacturing—the focus of this study—as well as three size groups that include all industries, not just manufacturing. Unsurprisingly, the internet is widely used for communication and market research. Additionally, a smaller share of companies rely on the internet to sell products, offer customer service, or provide training materials to employees.

[Table 1 about here.]

These activities suggest that broadband complements the non-routine cognitive work of non-production employees and those higher in the organizational hierarchy. Broadband lowers the cost of internal communication and improves non-production employees' ability to access information about products, markets, and consumers. Additionally, the activities in Table 1 suggest several opportunities for broadband to substitute for humans performing routine tasks, such as explaining a company's products to consumers and quoting prices.

A limitation of the survey results in Table 1 is that they cover high-level, general uses for the internet without addressing how broadband can change production activities.

[4]The survey did not ask specifically about broadband, but the data in Table 1 refer to 2008, when broadband was widespread, especially in large firms.

To gain further insight, I interviewed several managers in Brazil who offered specific examples of using broadband in production activities and to facilitate communication. A manufacturer of industrial equipment explained how broadband provided constant connectivity with their suppliers that allowed them to automate routine aspects of inventory management:

> "We scan the barcode on the kanban card and new part orders are sent directly to the supplier. This has saved time for the logistics people to spend more time on other tasks, like inventory optimization. It also means we've had some layoffs. We need fewer people to do ordering, and a different set of skills."

Consistent with task-based models (Autor et al. 2003), broadband in this firm substitutes for workers performing the routine task of calling suppliers to order parts. Additionally, it benefits high-skill workers by increasing the demand for non-routine activities like inventory optimization.

This same firm also used broadband to facilitate communication between workers directly involved in production and engineers and managers higher in the organizational hierarchy. Broadband, therefore, complemented the skills of engineers in the non-routine and ICT-intensive task of reviewing product design issues and communicating solutions:

> "The [machine] operator scans the production order and the computer downloads the CAD drawing from our database. We can share designs worldwide. If there is a problem, he can hit a button on the screen and report it to an engineer, who can diagnose and solve it."

This example illustrates how communication technology can facilitate centralization and effectively move problem solving up the organizational hierarchy (Garicano and Rossi-Hansberg 2006, Bloom et al. 2014). Before implementing this technology, the process of resolving issues was more time intensive. A machine operator would need to either personally resolve the problem or wait for a supervisor or engineer to physically walk to a machine. The ability to communicate remotely and exchange large product design files made it easier for engineers to solve problems and freed up the time of employees higher in the organization, allowing them to spend more time on advanced tasks. According to theories of "management by exception," the ability to consult an engineer by pressing a button can make it less important for machine operators to know how to solve problems. This makes worker skill less important, and according to theory, reduces wage inequality among workers.

Other examples include a provider of medical imaging services using broadband to automate appointment scheduling (eliminating the routine task of finding open dates over the phone), unifying databases across multiple work sites (allowing managers to remotely access information), and connecting bottling machines to a supplier so that their performance can be remotely monitored (eliminating the routine task of documenting and recording information while making less routine activities, like developing software for the machines, more valuable).

4 Data

To estimate the effects of broadband adoption on wages and inequality, I combine individual-level data on wages and workers' characteristics from an employer-employee matched dataset from Brazil with establishment-level data on broadband use from an annual survey of ICT. Additionally, I use occupation codes in the employer-employee matched data to link each job with its task requirements in O*NET, identify jobs that require using ICT, and assign each employee to a hierarchical level (e.g., production worker versus manager). I describe each data source in more detail below.

4.1 Employer-Employee Matched Data

Data on individual workers come from the *Relação Anual de Informações Sociais* (RAIS) for the years 2000 through 2008. RAIS is an employer-employee matched census of all employers in Brazil's formal economy conducted annually by Brazil's Ministry of Labor, the *Ministério do Trabalho e Emprego* (MTE). Participation is mandatory. Unique identifiers for workers and establishments in RAIS allow records to be linked across years. Employee records include data on wages, occupation, education, experience, age, gender, and contract hours. I limit my study to manufacturing establishments—which is the largest industrial sector in the data—so that analyses of the task content of jobs and occupational hierarchy can be more easily interpreted.

4.2 Broadband Adoption

I combine the employer-employee matched data from RAIS with establishment-level data on broadband adoption from the Latin American version of the Ci Technology Database (CiTDB) from Aberdeen Group. The European and U.S. versions of CiTDB—formerly called Harte Hanks—have been used in prior studies to measure internet technology adoption (Forman 2005, Forman et al. 2005, 2012, Bloom et al. 2014).[5] CiTDB contains information on communication technologies used by establishments (e.g., xDSL, T1, etc.), which I use to measure broadband adoption.[6] In line with prior work, I define broadband as use of an "always on" communication technology capable of speeds exceeding 256 kbit/s (Akerman et al. 2015, Czernich et al. 2011).

[Figure 1 about here.]

[5] CiTDB and Aberdeen Group were formerly owned by Harte Hanks; Halyard Capital acquired Aberdeen and CiTDB in April 2015.

[6] Unlike the U.S. and European version of CiTDB, the Latin American version lacks extensive data on the use of software. Furthermore, the availability of IT data changes year-to-year, which complicates the construction of longitudinal measures. The variables I use to measure broadband adoption, however, are stable across years.

Figure 1 shows that broadband use increased substantially from 2000 to 2008; fewer than 20 percent of the sample establishments used broadband in 2000, but nearly 70 percent had a broadband connection by the end of the sample period. Note that these numbers are not necessarily representative of all Brazilian manufacturing firms; the firms included in CiTDB are larger than the average firm in Brazil.

Table 2 presents worker-level summary statistics for the merged dataset. About half of observations are for people working in establishments that use broadband.

[Table 2 about here.]

4.3 Occupation Task Requirements

To examine how the effects of broadband vary for workers performing routine versus non-routine tasks (Hypothesis 1), I use measures from the U.S. Department of Labor's O*NET database to characterize the importance of various tasks for each occupation. O*NET contains hundreds of scales that rate the importance of various activities, skills, abilities, and work contexts for each job. For consistency with prior research and to limit researcher degrees of freedom in picking from hundreds of O*NET scales (Autor 2013), I use the same variables as Acemoglu and Autor (2011) and computer code from David Autor's website[7] to produce four measures of the extent to which each occupation involves various tasks:

1. Non-routine cognitive
2. Non-routine manual
3. Routine cognitive
4. Routine manual

Each of these variables is standardized across occupations so that a unit increase equals

[7] Available at `https://perma.cc/B7SK-VKUV`.

a one standard deviation increase in the extent to which an occupation depends on the given tasks relative to other occupations. Appendix A lists the specific O*NET scales used for each task measure. Table 3 shows the distribution of the task measures across Brazilian workers. The means and medians for the cognitive (manual) scales are negative (positive), reflecting the greater prevalence of workers engaged in manual-task-intensive occupations in Brazil's manufacturing sector.

[Table 3 about here.]

O*NET scales were developed to measure features of U.S. occupations, but have been used in prior studies of jobs in Brazil (Almeida et al. 2017, Nogueira Maciente 2019). I adapt the O*NET measures to Brazil by merging the Brazilian occupation codes to the U.S. codes using a crosswalk developed by Nogueira Maciente (2019).[8] Brazil's occupation coding scheme changed in 2003, but there is an official crosswalk allowing for conversion between the old (CBO 1994) and new (CBO 2002) systems. When conducting analyses that rely on occupation-level measures developed for the later scheme (CBO 2002), I convert the older occupational codes (covering 2000–2002) to the newer codes (covering 2003–2008) using the official crosswalk. I then separately analyze both the full sample period from 2000–2008 as well as the shorter period from 2003–2008 to ensure my results are not driven by quirks of the conversion process.

4.4 Occupation ICT Use

To further examine heterogeneity in the effects of broadband across workers performing different tasks (Hypothesis 2), I measure whether an occupation requires use of a computer

[8] Results based on merging the Brazilian codes to O*NET using crosswalks to the International Standard Classification of Occupations (ISCO 88) and a concordance developed by Muendler et al. (2004) as an intermediate step are qualitatively similar, although slightly *larger* in magnitude. I prefer the mapping created by Nogueira Maciente (2019) because it results in a finer, more accurate, and more detailed mapping than using ISCO 88 as an intermediate step.

or the internet using data from Brazil's Ministry of Labor (MTE). MTE produces lists of common "tools" for each occupation code. I identify every tool that mentions the word computer and classify jobs using these tools as "computer jobs."[9] Additionally, I identify every tool that mentions "internet", "intranet", or "extranet" and classify these as "internet jobs."

4.5 Organizational Hierarchy

I use occupation codes from RAIS to divide each establishment's workforce into hierarchical layers. My approach mirrors the method used by Caliendo et al. (2015) in their study of French manufacturers. Specifically, each worker is assigned to one of six groups:

1. Directors[10] (e.g. Chief Executive Officer, Chief Financial Officer)
2. Managers (e.g. Sales Manager, Branch Manager)
3. Supervisors (e.g. Foreman, Logistics Supervisor)
4. Professionals (e.g. Operations Engineer, Accountant)
5. Technicians (e.g. Forklift Operator, Machine electrician)
6. Workers (e.g. Welder, Production Line Feeder)

Like Caliendo et al. (2015), I find the grouping of occupations into layers reflects meaningful differences between employees. Table 4 shows the mean and selected percentiles of the wage distribution by layer. Directors and managers have higher wages than supervisors and professionals, who have higher wages than technicians and workers (at all percentiles).

[Table 4 about here.]

[9] Example tools include "computer", "microcomputer", and "computer software." Jobs requiring these tools are labeled "computer jobs."

[10] The word *diretor* in Portuguese refers to a high-level manager, not a member of the company's board of directors.

As a group, professionals do not cleanly fit between managers and workers in the hierarchy of manufacturing firms and their placement below supervisors above is arbitrary. Supervisor positions typically involve directly managing people engaged in production while reporting to a higher-level manager. While this is also true of some professional roles (see the description of engineers helping workers solve problems in Section 3), many are focused on non-production tasks like accounting and marketing. Tests of Hypotheses 3–4 regarding the effects of broadband on different levels of the organizational hierarchy thus focus on the distinction between clear managerial roles (directors, managers, and supervisors) and clear production roles (technicians and workers).

5 Methodology

I use a staggered difference-in-differences research design to measure the effects of broadband on wages by comparing firms that did and did not adopt broadband between 2000 and 2008. My estimands of interest are the average treatment effect of broadband on the treated and treatment effects conditional on job characteristics (such as the importance of non-routine tasks and position in the organizational hierarchy; see Hypotheses 1–3). Additionally, I use grouped quantile regression estimators to recover the effects of broadband on selected quantiles of the within-establishment wage distribution (Chetverikov et al. 2016), which are informative for testing predictions regarding the effects of CT on inequality at different levels of the organizational hierarchy (Hypothesis 4).

The starting point for these analyses is the two-way fixed effects estimator, allowing the effect of broadband to differ by occupation characteristics:

$$\ln w_{ijt} = \beta_0 D_{jt} + \beta_1' D_{jt} * K_{it} + \theta' K_{it} + \delta' X_{ijt} + \gamma L_{jt} + \alpha_j + \lambda_{\kappa(j)t} + \epsilon_{ijt} \tag{1}$$

where w_{ijt} is the real wage of worker i at establishment j in year t. D_{jt} is an indicator variable for broadband use by establishment j, and K_{it} is a vector of occupation attributes (e.g. task measures, IT-intensity, an indicator being a manager) for worker i's occupation in year t. For example, task measures included in K_{it} capture the extent to which a worker's job involves routine vs. non-routine and cognitive vs. manual tasks. Coefficients on interactions of occupation attributes with broadband (β_1) capture how the effect on wages varies with features of the job that a worker performs. The vector X_{ijt} is a set of time-varying worker covariates that includes education, current job experience, sex, age, age-squared, and log contract hours (see Table 2 for summary statistics). In some specifications, I also include log employment, L_{jt}, to control for the possibility that larger establishments pay higher wages and are more likely to adopt broadband (Oi and Idson 1999). Employment, however, could itself be affected by broadband adoption; I therefore omit it from my preferred specifications. The model includes both establishment (α_j) and industry-year ($\lambda_{\kappa(j)t}$, where $\kappa(j)$ is the industry of establishment j) fixed effects that control for unobserved establishment heterogeneity and annual shocks that affect all workers within an industry.[11]

A key assumption of the above model is that wages in firms that do and do not adopt broadband would evolve similarly in the absence of broadband. I present support for this assumption in Section 6.1, and I conduct several robustness checks in Section 7 to ensure my results are not driven by violations of the parallel trends assumption or omitted variables that affect broadband adoption and wages.

5.1 Quantile analyses

Combining employer-employee matched data with information on broadband use over time allows me to examine how the full wage distribution within establishments (or hierarchical

[11] I estimate the model using the estimator from Correia (2016) and cluster standard errors by establishment in all analyses.

levels of establishments), rather than the average wage, changes following broadband adoption, which is essential for testing Hypothesis 4 regarding inequality at different levels of the organization. To do so, I implement the grouped quantile regression approach from Chetverikov et al. (2016). This estimator allows researchers to examine how a group-level "treatment" affects the distribution of micro-level outcomes across individuals within a group. In my setting, the "groups" are establishment-year (or establishment-year-hierarchy level) observations, the "treatment" is broadband adoption, and the micro-level outcomes are the wages of individual workers. Specifically, I estimate:

$$Q_{\ln w_{ijt}|D_{jt},\eta_{jt}}(\tau) = \alpha_j(\tau) + \lambda_{\kappa(j)t}(\tau) + \beta(\tau)D_{jt} + \epsilon(\tau, \eta_{jt}) \tag{2}$$

where $Q(\tau)$ selects the τth quantile of log wages for group j in year t, D_{jt} is an indicator for establishment broadband adoption, and α_j and $\lambda_{\kappa(j)t}$ are establishment (or establishment-level) and industry-year fixed effects. This analysis is limited to groups with at least 30 micro-level observations (i.e., establishment-years and establishment-year-hierarchy levels with at least 30 employees) so that there are enough observations to estimate effects on distinct quantiles of the wage distribution.

Greater effects of broadband ($\beta(\tau)$) in the upper quantiles of the wage distribution than in lower quantiles indicate that inequality within establishments or hierarchical layers increases following broadband adoption. In contrast, greater effects of broadband on lower quantiles suggest inequality decreases. Hypothesis 4 predicts the former pattern will hold for managers—inequality will increase among managers— while the latter pattern will hold for workers—inequality will decrease among workers.

6 Results

6.1 Average Effects

On average, wages increase 2.2 percent following broadband adoption. Table 5 shows the effect of broadband adoption without distinguishing between occupations or types of employees. The results in columns 2–3 include establishment and year fixed effects, while columns 4–5 include establishment and industry-year fixed effects. The estimates are stable across specifications and show a positive average effect of broadband adoption on wages. Comparing the results of columns 2 and 4 with those of columns 3 and 5 shows that the estimate of the broadband effect is insensitive to controlling for the number of employees in an establishment. The increase in wages following broadband adoption, therefore, is not explained by bigger, growing establishments paying both higher wages and simultaneously choosing to adopt broadband.

[Table 5 about here.]

There are several caveats to a causal interpretation of these results. First, firms might increase wages for other reasons that happen to coincide with broadband adoption. Without controlling for these omitted factors, wage increases will be erroneously attributed to broadband. Second, even if broadband causes wages to increase, the firms most likely to benefit from the technology will be more likely to adopt (Forman 2005). For this reason, the estimates should be interpreted as an average treatment effect on the treated rather than a population average treatment effect. Third, trends in wages prior to broadband adoption might be different from trends in wages at firms that do not adopt, which would violate the parallel trends assumption underlying difference-in-differences models. If this were the case, firms that do not adopt broadband would be a poor control group for the adopters.

[Figure 2 about here.]

I take several steps to address these concerns. First, I investigate how the wage effects of broadband vary across workers with different attributes. The heterogeneity in wage effects across workers (described below) is consistent with wages changing in response to broadband adoption, which partially mitigates concerns about omitted variable bias. However, I further investigate omitted variable bias in Section 7.3 by calculating the degree of selection on unobservables that would be needed for the broadband effect to be zero using the method of Oster (2019). I find that selection on unobservables is unlikely to explain the results.

Second, I examine wage trends prior to broadband adoption by estimating a modified version of the model in column 4 of Table 5 that includes separate indicator variables for years before and after broadband adoption. Figure 2 plots coefficient estimates from this model using the estimator of Sun and Abraham (2021) to adjust for variation in the timing of broadband adoption. These single-year estimates show that wage increases happen in the years following broadband adoption. There are no statistically significant "effects" of broadband on wages prior to adoption and the pre-period coefficient estimates are close to zero, suggesting no strong deviation in pre-trend between adopters and non-adopters of broadband technology.

I further examine the robustness of the results in Section 7 by conducting placebo tests for each of the analyses, omitting firms that never adopt broadband during my sample period, and limiting the sample to a brief period before and after adoption. Each of these tests suggests that the results are not driven by a violation of the parallel trends assumption, or (omitted) variables that affected wages in the years after broadband adoption.

6.2 Effects by Occupation Characteristics

The effect of broadband is heterogeneous. Consistent with Hypothesis 1, workers in occupations that require more non-routine cognitive tasks see larger wage gains than workers in occupations that are intensive in routine cognitive tasks. Table 6 shows regressions in which broadband adoption is interacted with occupation-specific measures of task intensity. Columns 1–2 show results for the full sample period, while columns 3–4 present results for 2003–2008 because the occupation coding system changed in 2003 (see Section 4.3 for further explanation). The coefficients on non-routine cognitive and routine cognitive tasks have opposite signs, suggesting that broadband complements workers performing non-routine cognitive tasks and substitutes for workers in routine cognitive tasks. A one unit increase (roughly one standard deviation) in the intensity of non-routine cognitive tasks implies an additional 2–3 percent wage increase following broadband adoption. In contrast, a one unit increase in the intensity of routine cognitive tasks implies a 2.5 percent decrease in wages, which nearly cancels out the baseline increase of 3 percent from broadband adoption. The difference between the coefficients on the interactions of broadband with non-routine and routine cognitive tasks is statistically significant at the 0.01 level in columns 1–2 and at the 0.05 level in columns 3–4.

[Table 6 about here.]

Table 6 also indicates that the effect of broadband adoption does not vary in the intensity of manual tasks. This is consistent with the intuition that broadband ought to have small, if any, effect on tasks that require interaction with equipment and using one's hands.

[Table 7 about here.]

The use of four, continuous task measures interacted with broadband complicates interpretation of the results in Table 6. Table 7 therefore presents the distribution of wage effects (across workers) implied by the task regressions. For each worker, I use the coefficients from the regressions in Table 6 and the task intensities of the worker's occupation to calculate the hypothetical impact of broadband for that worker. I then summarize the distribution of these wage effects across all workers. The results in Table 7 show that the effect of broadband on real wages is positive for the majority of workers and that wage gains in the right tail of the distribution are much larger in magnitude than any wage losses in the left tail.

[Table 8 about here.]

To test Hypothesis 2 and further examine the prediction that broadband complements workers performing certain tasks, I interact broadband adoption with indicators for on-the-job use of information and communication technology (see Section 4.4 for an explanation of the data). Table 8 shows estimates of Equation 1 including these interactions. The analysis is split into two time periods because the occupation coding scheme changed in 2003 and the measures of on-the-job ICT use were developed for the later scheme (see Section 4.3 for further explanation). The results in columns 3 and 4 use only these later occupation codes and include a 6-digit occupation code fixed effect to account for the fact that ICT-intensive jobs likely differ on dimensions other than computer and internet use. To show that the results also hold for the longer (2000–2008) sample period, however, I match occupation codes from the earlier coding scheme to the newer scheme using an official crosswalk. I then estimate the models (columns 1–2) without the occupation fixed effect, but including a fixed effect for the 6 broad job categories (director, manager, supervisor, professional, technician, and worker) described in Section 4.5, and see similar results.[12]

Consistent with Hypothesis 2, Table 8 shows that the effect of broadband on wages is greatest for workers in occupations that commonly require using a computer or the inter-

[12] Including the 6-digit occupation fixed effect is not possible for the 2000–2008 sample period because the mapping of occupation codes from the older to the newer scheme is not one-to-one. When measuring computer and internet use for these occupations I therefore assign the "computer job" and "internet job" dummies to 1 if at least half the code matches suggest the occupation commonly requires using these tools.

net. The baseline impacts of broadband adoption are roughly 1–2 percent, but workers in occupations that use ICT see gains of 4–6 percent.

Beyond providing support for Hypothesis 2, this finding alleviates at least some concerns that unobserved variables besides broadband adoption are responsible for the measured wage increase. For an omitted variable to explain the results of Tables 6–8, it must be correlated with broadband adoption and also mostly affect the wages of workers doing non-routine cognitive tasks in occupations that commonly require using a computer or the internet.

The results of Tables 5–8 are broadly consistent with those of other studies of broadband that use worker-level data. Akerman et al. (2015) find that broadband in Norway raises the wages of high-skill workers performing abstract tasks and decreases the wages of low-skill workers performing routine tasks.[13] Their effects are similar in magnitude to those reported in Tables 6-7. Examining studies specific to Brazil, my estimates for the wage effects of broadband are larger, although roughly similar in magnitude, to those of Dutz et al. (2017), who examine the regional wage effects of Brazil's internet (but not specifically broadband) rollout. They report a two-year cumulative wage increase of 4.1–4.8 percent for middle- and high-skill occupations in manufacturing in response to an increase in internet access, but no wage effect for low-skill occupations.[14] A possible explanation for the slightly larger effect estimates in this paper is that, unlike Dutz et al. (2017), I observe the adoption decisions of individual firms instead of relying on measures of regional broadband availability. Almeida et al. (2017) similarly examine regional variation in internet availability in Brazil and find that internet expansion decreases labor demand for routine tasks. This finding is consistent with the pattern of results in Table 6,

[13] Akerman et al. (2015) use a different classification of tasks into abstract, routine, and manual categories. The interpretation, however, is similar.

[14] Internet access in Dutz et al. (2017) is measured using the share of schools with internet in each municipality. The reported effects are based on increasing internet access from 0 to 100 percent (i.e. going from no access to every school having access).

although Almeida et al. (2017) do not examine wage outcomes.

6.3 Wage Effects and Organizational Hierarchy

Wage increases following broadband adoption are greatest for workers higher in the organizational hierarchy: directors and managers see larger increases than lower-level workers (Hypothesis 3). Columns 1 and 4 of Table 9 show that directors and managers earn about 7–8 percent more following broadband adoption compared to a main effect of just over 2 percent for all employees.

[Table 9 about here.]

The effect of broadband is especially large for directors at the top of the organizational hierarchy. Columns 2–3 and 5–6 split the managers and directors group into two separate coefficients, and columns 3 and 6 add another coefficient for supervisors, who are grouped with workers in the other columns. The estimates suggest that directors earn 17 percent more following firm adoption of broadband. This is about 9 percentage points more than the increase for managers. Most firms in the sample are private companies. The directors in this sample are therefore more likely to have a large ownership stake in the firm than if the firms were public. The wage increases for directors are large, but potentially consistent with firm owners capturing large gains as a result of broadband increasing firm productivity. Unfortunately, I do not have data on revenue or non-labor inputs to explore this hypothesis. Akerman et al. (2015), however, report that firms in Norway earn large rents from broadband adoption, and Jung and López-Bazo (2017) find a positive effect of broadband on regional productivity in Brazil.

The greater effect of broadband for directors and managers implies that within firm wage inequality between levels of the organizational hierarchy increases following adoption. To more thoroughly examine this pattern, however, I use the grouped quantile regression estimator from Chetverikov et al. (2016) to assess how broadband adoption affects the full distribution of wages within establishments and each level of the organizational hierarchy (see Section 5.1).

Figure 3a plots the effect of broadband on selected quantiles of the wage distribution, estimated using Equation 2. Although the estimates for the individual quantiles are imprecise, the pattern of point estimates in Figure 3a suggests that broadband has larger effects on the right tail of the wage distribution than on wages in the left tail. In other words, high-wage workers benefit more than low-wage workers from broadband adoption and inequality within firms increases.

[Figure 3 about here.]

Figure 3b extends this analysis to test Hypothesis 4 by separately examining changes in the wage distribution across levels of the organizational hierarchy. Confidence intervals are omitted for clarity and Table 10 presents coefficients and standard errors for Figure 3 at selected quantiles. The pattern of coefficients for lower levels of the hierarchy (technicians and workers) is flatter than the pattern for upper levels (managers).[15] The coefficients for workers are flat or decreasing over upper percentiles of the wage distribution, which indicates that wage inequality among workers decreases following broadband adoption. The coefficients for managers, in contrast, increase steeply as one moves from the lower to the upper percentiles, indicating that inequality increases among managers because the wage gains in the right tail of the distribution are much larger than those in the left tail.

[Table 10 about here.]

This pattern is generally consistent with theories of "management by exception" regarding the effects of CT on inequality at different levels of the organizational hierarchy

[15]The managers group in Figure 3b includes directors, managers, and supervisors. Pooling these manager types is necessary to ensure there are enough observations within each layer to estimate effects on separate quantiles of the wage distribution.

(Hypothesis 4). Broadband benefits managers more than workers and increases inequality among managers more than workers.

7 Robustness Checks and Alternative Explanations

This section presents several robustness checks related to the difference-in-differences estimation strategy and possible alternative explanations for the results. Figure 2 suggests that pre-trends in average wages are similar for firms that do and do not adopt broadband. In this section, I conduct several supplementary analyses to further examine the parallel trends assumption as well as the robustness of the results to omitted variables and alternative explanations.

7.1 Placebo Analyses and Parallel Trends

[Table 11 about here.]

[Table 12 about here.]

I conduct a placebo analysis to further examine the parallel trends assumption and potential impact of differential trends in wages on the estimates in the above tables. Table 11 reports summary statistics for the distribution of 300 placebo coefficient estimates. These estimates are produced by randomly assigning firms that adopted broadband a new, fake adoption date that pre-dates the true year of adoption and re-estimating the model for wages (excluding the actual post-adoption years). The relatively small number of pre- and post-adoption years in my sample as well as the possibility for dynamic effects following broadband adoption preclude estimation of firm-specific trends (Wolfers 2006). This placebo analysis, however, offers an alternative and has the advantage of detecting non-linear differences in the pre-trends of adopting and non-adopting firms. If adopting firms had increasing wages relative to non-adopting firms prior to broadband adoption, then the placebo difference-in-differences analysis would show a positive effect of placebo broadband adoption on wages. The results in Table 11 show, however, that there is no effect of placebo broadband adoption. The placebo estimates are centered around zero. For example, the first row—based on the model from column 4 of Table 5—shows a mean placebo estimate of -0.005 and an actual estimate of the coefficient on broadband (0.022) that exceeds more than 95 percent of the placebo estimates.

Results for placebo analyses of broadband interacted with occupation tasks (Table 6), use of information technology (Table 8), and position in the organizational hierarchy (Table 9) are similar (see Table 11). The placebo estimates are indistinguishable from zero, and the statistically significant positive (negative) coefficients in the previous tables exceed (are less than) the 95th (5th) percentile of the placebo estimates. These results lend credibility to the parallel trends assumption underlying the difference-in-differences analyses and suggest that the results reporting a significant impact of broadband on wages are not driven by pre-trends in wages at the adopting firms.

Table 12 repeats the placebo analysis exercise for the quantile regression results and presents estimates for the 10th, 50th, and 90th percentile of the wage distribution. The results are somewhat noisier than for the main analyses due to the smaller sample size used for the quantile analyses, but the true estimates at upper quantiles of the wage distribution (e.g., the 90th percentile) exceed the 95th percentile of the placebo estimates, except for workers. Consistent with theory and the main results, workers have larger effect sizes at lower quantiles of the wage distribution while managers and professionals see larger wage increases in the upper quantiles (see Figure 3b).

7.2 New Versus Existing Employees

The effect of broadband on new employees is the same as the effect on existing employees. This suggests that wage increases from broadband adoption are not driven by firms recruiting better workers post-adoption. Table 13 shows the effect of broadband adoption on wages allowing for the effect to differ by whether an employee is in his first, first two, or first three years of working at the establishment. The results show that newly hired employees do not earn an additional wage premium from broadband adoption over that earned by existing employees.

[Table 13 about here.]

7.3 Assessing Omitted Variable Bias

It is possible that unobservables correlated with broadband adoption and wages bias the estimates. One potentially important omitted variable that would be consistent with the results in Tables 5–8 is unobserved ICT investments that accompany broadband adoption. To assess this potential bias, I use the methodology of Oster (2019), who provides a method for comparing coefficients and R^2 values from regressions with and without controls to calculate the degree of bias (δ) from omitted variables that would be necessary for the effect of broadband on wages in column 3 of Table 5 to be zero. A δ that equals 1 implies that selection on unobservables has the same effect on the broadband coefficient as selection on observables (i.e., worker characteristics). This is the threshold value suggested by Oster (2019) for assessing "robustness." Calculating δ requires making an assumption about the R^2 of a hypothetical regression of wages on both the observables and unobservables, which Oster (2019) labels R_{max}.[16] She suggests using $R_{max} = 1.3R^2$ from the sample regression with controls.

[Figure 4 about here.]

Figure 4 shows the values of δ (y-axis) necessary to explain away the broadband effect under different assumptions about R_{max} (x-axis). In all cases, values of δ exceed 1 (the

[16] As Oster (2019) points out, this value may be less than 1 due to measurement error.

horizontal line) and the minimum value (at $R_{max} = 1$) is slightly above 2. This implies that selection on unobservables like complementary ICT investments would need to be more than twice as important as selection on observable worker characteristics for the effect of broadband on wages to equal 0. Thus, omitted variable bias is an unlikely explanation for the results.

7.4 Firms that Never Adopt Broadband

Most firms in my sample eventually adopt broadband (Figure 1), which partially alleviates concerns regarding the selection of firms into using broadband. In Appendix B, however, I reproduce the main results after excluding firms that I never observe using broadband. Coefficient estimates using this smaller sample of eventual adopters are similar in magnitude to those from the full sample. Note that it is not *a priori* clear whether firms that never adopt broadband are poor controls for firms choosing to adopt the technology; the results of the placebo analyses in Table 11 suggest that pre-trends in wages between adopters and non-adopters are indeed similar when using the full sample. Furthermore, excluding never adopters from the analysis can have negative consequences for identification as they provide information about wage dynamics in the absence of broadband (Borusyak and Jaravel 2016, Sun and Abraham 2021).

7.5 Restricting the Pre- and Post-Adoption Period

One concern with difference-in-differences estimates is that the model may attribute changes in wages caused by events that occur well after broadband adoption to the adoption event. Figure 2, however, shows that I observe an effect on wages soon after broadband adoption. To further support the claim that broadband increases wages, however, I reproduce the main results using at most four years before and after adoption. This ensures that my results are not driven by changes in wages that occurred well after (or before) broadband adoption. The coefficient estimates using this restricted sample period—presented in Appendix C—are similar in magnitude and statistical significance to the results using all available years.

8 Conclusion

Broadband is among the most important communication technologies of the past several decades, and public policy in both developed and developing countries aims to expand access to broadband technology with the goal of closing the "digital divide" and spurring economic growth (Kruger and Gilroy 2019). At the same time, other recent technological trends, such as computerization, are known to have contributed to a dramatic increase in inequality since the 1980s (Acemoglu 2002). Whether the results from studies of computerization apply to broadband, however, is a priori unclear. Theory suggests information technology (IT) and communication technology (CT) have different effects on wages and inequality, with CT like broadband reducing inequality among lower-level employees (Garicano and Rossi-Hansberg 2006). To date, empirical research has typically analyzed broadband at the macroeconomic, industry-, and region-level, finding that it has positive effects on average (Gillett et al. 2006, Czernich et al. 2011, Koutroumpis 2009), but that the gains are geographically concentrated (Forman et al. 2012). Fewer studies have examined heterogeneity in outcomes across workers, especially in developing countries (Hjort and Tian 2021), or tested the novel predictions from theories of "management by exception" regarding CT's effects on wages and inequality at different levels of the organizational hierarchy (Garicano and Rossi-Hansberg 2006, Bloom et al. 2014, Garicano and Rossi-Hansberg 2015).

I link micro-level, employer-employee matched data from Brazil with longitudinal, establishment-level data on broadband adoption to study heterogeneity in broadband's effects. Overall, wages increase 2.2 percent following broadband adoption, but not all workers benefit equally. Consistent with theories of biased technical change (Autor et al. 2003, Acemoglu and Autor 2011), wages increase more for workers engaged in non-routine cognitive tasks and tasks requiring the use of ICT. Consistent with theories of "management by exception" (Garicano and Rossi-Hansberg 2006), wages increase more for managers than for workers and inequality among managers (workers) increases (decreases). Despite these differences in the benefits of broadband, I find that few, if any, workers experience real wage decreases following broadband adoption.

The results of this study provide one of the first tests of the unique predictions of theories of "management by exception" regarding technology's effects on wages. Additionally, the results extend research on the distributional effects of broadband by examining worker-level outcomes in a novel, developing country context. In doing so, I contribute to research on the wage effects of internet technology (Gillett et al. 2006, Forman et al. 2012, Kolko 2012, Akerman et al. 2015, Ivus and Boland 2015, Almeida et al. 2017, Dutz et al. 2017, Hjort and Poulsen 2019), as well a a wider literature on impacts of the internet that includes studies of education (Belo et al. 2013), fertility (Billari et al. 2019), and crime (Bhuller et al. 2013, Diegmann 2019), among other outcomes.

There are several important directions for future research. First, scholars should seek ways to further examine the distinct effects of IT and CT. These include not only effects on wages, but organizational outcomes such as firm size, scope, and span-of-control (Garicano and Rossi-Hansberg 2006). While a strength of this study is the ability to observe longitudinal data on technology use, I lack data to directly compare the effects of IT and CT. Additionally, detecting the effects of IT and CT on outcomes like span-of-control may require both larger samples than this study and the development of novel methods or survey instruments to measure reporting relationships within firms (Bloom et al. 2014). Second, although this study emphasizes changes in wages within firms, that is not the only possible mechanism through which technology can affect the wage distribution. Future studies should investigate the extent to which changes in the workforce and wages precipitated by technology occur between versus within firms (Benzell et al. 2019, Autor et al. 2020). Third, the fact workers do not benefit equally from broadband suggests future work is needed to understand whether public policies to close the "digital divide" could have greater impact by also making complementary investments in training, or reduce any negative impacts by pairing infrastructure spending with other social programs.

Appendices

A Construction of O*NET Task Measures

This appendix lists the O*NET scales used to construct the occupation task measures used in Table 6. The O*NET scales used in this paper are based on those in Acemoglu and Autor (2011) and computer code from David Autor's website.[17]

Acemoglu and Autor (2011) use two sub-measures of non-routine cognitive tasks: "analytical" and "interpersonal." For simplicity, I combine these two measures into a single non-routine cognitive measure.

The computer code provided by David Autor for constructing task measures includes two non-routine manual scales: "physical" and "interpersonal". The interpersonal scale, however, is not used in Acemoglu and Autor (2011). I therefore combine the two non-routine manual scales in the computer code into a single non-routine manual measure.

Non-routine cognitive

4.A.2.a.4 Analyzing data/information

4.A.2.b.2 Thinking creatively

4.A.4.a.1 Interpreting information for others

4.A.4.a.4 Establishing and maintaining personal relationships

4.A.4.b.4 Guiding, directing and motivating subordinates

4.A.4.b.5 Coaching/developing others

Non-routine manual

4.A.3.a.4 Operating vehicles, mechanized devices, or equipment

[17] Available at `https://perma.cc/B7SK-VKUV`.

4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls

1.A.2.a.2 Manual dexterity

1.A.1.f.1 Spatial orientation

2.B.1.a Social Perceptiveness

Routine cognitive

4.C.3.b.7 Importance of repeating the same tasks

4.C.3.b.4 Importance of being exact or accurate

4.C.3.b.8 Structured v. Unstructured work (reversed)

Routine manual

4.C.3.d.3 Pace determined by speed of equipment

4.A.3.a.3 Controlling machines and processes

4.C.2.d.1.i Spend time making repetitive motions

B Removing Firms that Never Adopt Broadband

This appendix presents results of the analyses after dropping firms that never adopt broadband during the sample period (2000–2008). If trends in wages differ between firms adopting and not adopting broadband, then difference-in-differences estimates from comparing these two groups will be biased. It is not *a priori* clear whether firms that never adopt broadband are a poor control group for firms choosing to adopt the technology. Results of the placebo analyses in Table 11, however, suggest that pre-trends in wages between adopters and non-adopters are indeed similar, which favors using the full sample of firms for the analyses. Furthermore, excluding never adopters from the analysis can have negative consequences for identification as they provide information about wage dynamics in the absence of broadband (Borusyak and Jaravel 2016).

Coefficient estimates based only off the sample of adopting firms are similar in magnitude to those from the full sample (Table 14). This further suggests that the results are not driven by different wage trends in firms that do and do not adopt broadband technology.

[Table 14 about here.]

C Restricting Sample Years

This appendix presents results of the analyses after limiting the sample to include at most 4 years before and after broadband adoption. One concern with difference-in-differences estimates is that the model may attribute changes in wages caused by events that occur well after broadband adoption to the adoption event.

Coefficient estimates including only years proximate to the broadband adoption event, however, are similar in magnitude to those from the full sample (Table 15). This pattern, combined with the fact that wage effects are observed soon after adoption (Figure 2), shows that the results are not driven by wage changes long after the year of broadband adoption, but instead closely follow the adoption event in time.

[Table 15 about here.]

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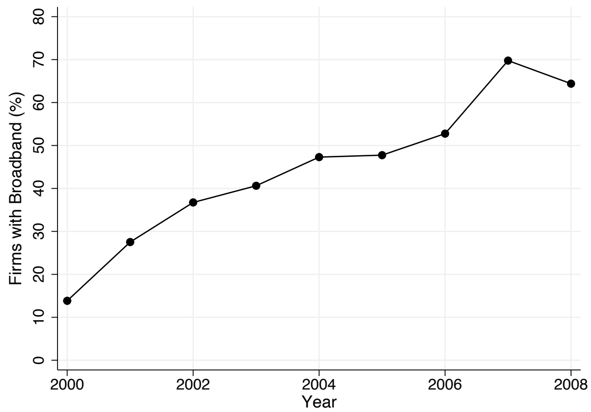
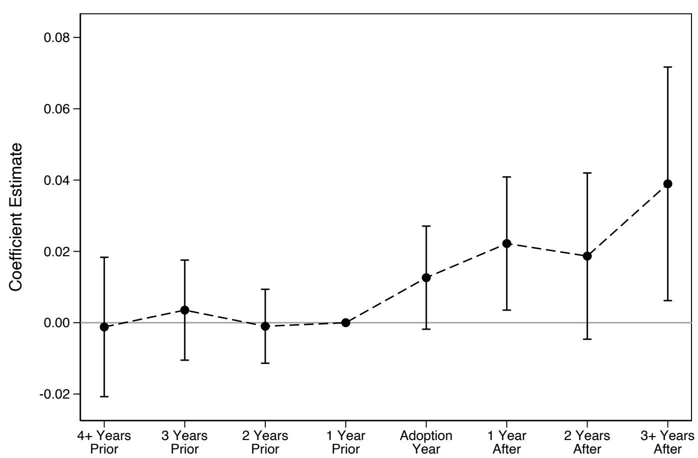
Figure 1: Adoption of Broadband



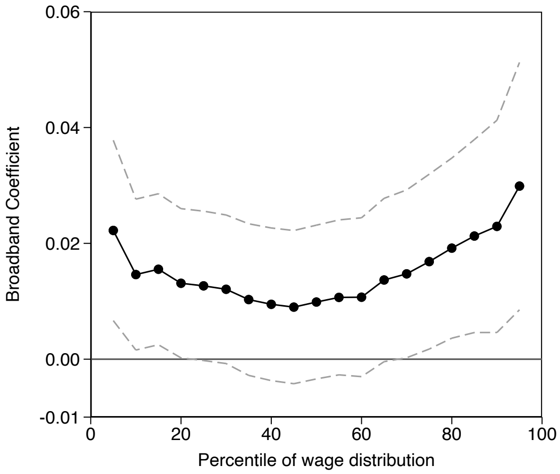
NOTE:

Figure 2: Wages Before and After Broadband Adoption

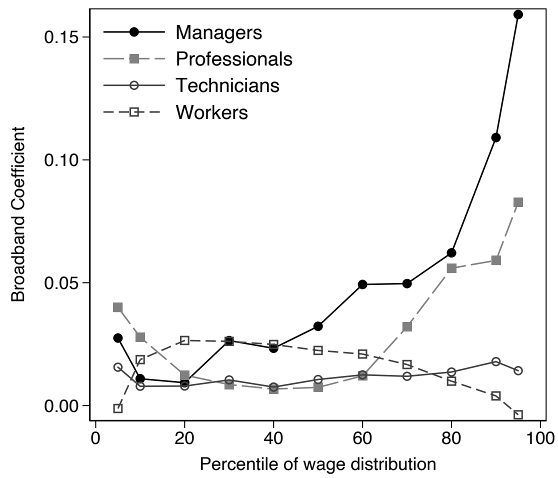


NOTE: Values along the x-axis represent time relative to broadband adoption; e.g. “2 Years After” refers to the second year following adoption.

Figure 3: Quantile Effects of Broadband Adoption



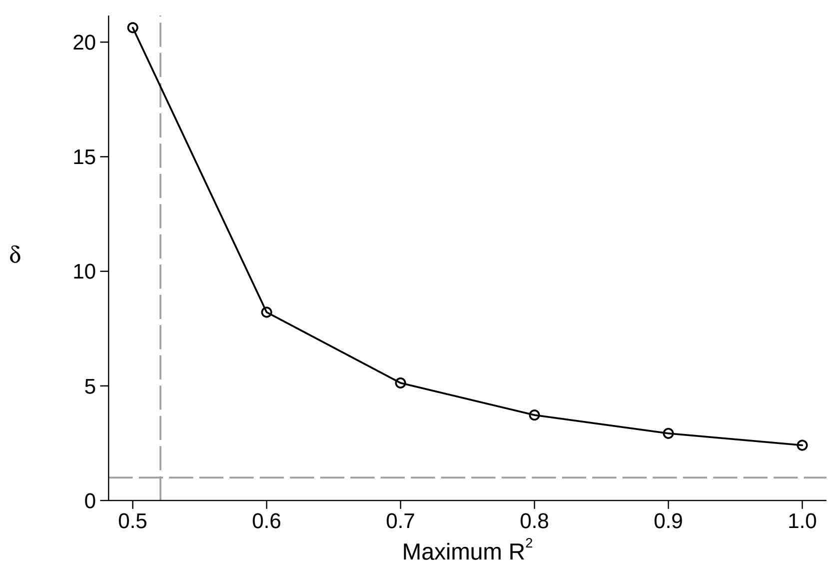
(a) Overall wage distribution



(b) Wage distribution by hierarchy level

NOTE: Coefficient estimates based on a model with establishment and industry-year fixed effects. Dashed lines represent the upper and lower bounds of the 95 percent confidence interval for the coefficient estimate.

Figure 4: Assessing Omitted Variable Bias



NOTE: Figure shows values of δ (the degree of selection on unobservables) necessary for the treatment effect of broadband in column 3 of Table 5 to equal 0 under different assumptions about R_{max}, the theoretical maximum value of R^2 (Oster 2019). The dashed horizontal and vertical lines correspond to Oster's (2019) suggested values of $1.3R^2$ (from the sample regression) and cutoff of $\delta = 1$.

Table 1: Internet Use in Brazilian Firms

Survey Item	Manufacturing	All Firms, by No. Employees 10–49	50–249	250+
Uses for the internet[1]				
Email	99	99	100	100
Research products and services	96	94	97	99
Other research	87	84	91	92
Monitor the market (e.g., prices)	70	67	78	82
Offer customer services	55	48	61	64
Training and education	28	29	37	56
Has company website	59	47	76	88
Company website features[2]				
Online product catalog	57	51	52	50
Post-sale support	36	35	35	34
Shopping cart	19	25	22	21
Online payment system	12	13	14	18

NOTE: *Source:* 2008 survey of firms with 10 or more employees by the Centro Regional de Estudos para o Desenvolvimento da Sociedade da Informação (CETIC). Numbers represent a percentage of companies.
[1] $N = 3,168$ companies with internet access.
[2] $N = 1,668$ companies with a website.

Table 2: Employee Summary Statistics

	mean	sd	p5	p10	p50	p90	p95
High-speed Internet	0.49	0.50	0	0	0	1	1
Log wage	7.05	0.82	6.0	6.1	6.9	8.2	8.6
Log contract hours	3.77	0.09	3.7	3.7	3.8	3.8	3.8
Tenure in months	60.5	70.7	1.9	3.5	33	162	211
Age	33.1	10.1	20	21	32	47	52
Female	0.24	0.43	0	0	0	1	1
Education Dummies							
Below Elementary	0.08	0.27	0	0	0	0	1
Elementary	0.09	0.29	0	0	0	0	1
Some Middle	0.14	0.35	0	0	0	1	1
Middle	0.15	0.36	0	0	0	1	1
Some High	0.11	0.31	0	0	0	1	1
High School	0.30	0.46	0	0	0	1	1
Some College	0.05	0.21	0	0	0	0	0
Higher Ed Degree	0.08	0.28	0	0	0	0	1

NOTE: Observations are employee-employer matched records from manufacturing firms in RAIS merged with data on broadband usage from CiTDB. Log wages are log of mean monthly wage in 2008 reais.

Table 3: Task Summary Statistics

Task measure	mean	sd	p5	p10	p50	p90	p95
Non-routine cognitive	-0.51	0.76	-1.44	-1.35	-0.41	0.51	0.94
Non-routine manual	0.37	0.84	-0.91	-0.64	0.25	1.70	1.70
Routine cognitive	-0.03	0.84	-1.20	-0.83	-0.16	1.32	1.43
Routine manual	0.84	0.93	-0.91	-0.45	1.01	2.07	2.07

NOTE: Table shows distribution of occupation-level task measures across workers in the sample of manufacturing firms.

Table 4: Wage Distribution by Hierarchy Level

	Director	Manager	Supervisor	Professional	Technician	Worker
mean	17,954	8,666	3,777	4,660	1,785	1,037
p5	1,604	1,029	724	1,068	486	348
p10	3,019	1,672	973	1,432	589	412
p25	7,535	3,436	1,672	2,334	813	544
p50	16,608	7,139	2,961	3,783	1,252	758
p75	26,304	11,770	4,999	5,952	2,093	1,181
p90	35,228	17,162	7,410	8,621	3,494	1,869
p95	40,091	21,749	9,219	10,849	4,732	2,538

NOTE: Wages are mean monthly wage in 2008 reais.

Table 5: Wage Effects of Broadband

	(1)	(2)	(3)	(4)	(5)
Broadband	0.032***	0.024***	0.025***	0.022***	0.022***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Log Employees			0.000		-0.010**
			(0.004)		(0.004)
Worker Controls		•	•	•	•
Fixed Effects					
Establishment	•	•	•	•	•
Year	•	•	•		
Industry-Year				•	•
Adj-R^2	0.45	0.69	0.69	0.69	0.69
Establishments	3,349	3,349	3,334	3,348	3,333
N	6,516,495	6,515,675	6,464,730	6,515,673	6,464,728

NOTE: Standard errors in parentheses are clustered by establishment.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Wage Effects of Broadband by Tasks

	Full Sample, 2000–2008		Years 2003–2008	
	(1)	(2)	(3)	(4)
Broadband ×				
Intercept	0.030***	0.035***	0.031**	0.034**
	(0.010)	(0.010)	(0.013)	(0.013)
Non-routine cognitive	0.033***	0.028**	0.024*	0.022*
	(0.011)	(0.011)	(0.013)	(0.013)
Non-routine manual	0.007	0.000	-0.001	-0.005
	(0.007)	(0.006)	(0.007)	(0.007)
Routine cognitive	-0.031***	-0.027***	-0.026**	-0.023**
	(0.009)	(0.009)	(0.010)	(0.010)
Routine manual	0.010	0.008	0.003	0.002
	(0.007)	(0.007)	(0.009)	(0.009)
Non-routine cognitive	0.189***	0.192***	0.198***	0.199***
	(0.008)	(0.008)	(0.010)	(0.010)
Non-routine manual	-0.066***	-0.063***	-0.062***	-0.060***
	(0.005)	(0.004)	(0.005)	(0.005)
Routine cognitive	-0.038***	-0.040***	-0.046***	-0.048***
	(0.006)	(0.006)	(0.008)	(0.008)
Routine manual	-0.045***	-0.044***	-0.036***	-0.036***
	(0.005)	(0.005)	(0.007)	(0.007)
Worker Controls	•	•	•	•
Fixed Effects				
Establishment	•	•	•	•
Year	•		•	
Industry-Year		•		•
Adj-R^2	0.71	0.72	0.73	0.73
Establishments	3,348	3,348	2,673	2,673
N	6,222,280	6,222,280	3,998,747	3,998,747

NOTE: Standard errors in parentheses are clustered by establishment. Differences between the impact of broadband on non-routine and routine tasks are statistically significant at the 0.01 level in the models using the full sample period (columns 1 and 2), and significant at the 0.05 level for the models covering 2003–2008 (columns 3 and 4).

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Summary of Wage Effects of Broadband by Tasks

Model	mean	sd	p5	p10	p25	p50	p75	p90	p95
(1)	0.026	0.025	-0.018	-0.004	0.012	0.027	0.037	0.062	0.069
(2)	0.028	0.019	-0.002	0.006	0.017	0.029	0.035	0.055	0.062
(3)	0.021	0.019	-0.003	-0.002	0.009	0.021	0.028	0.045	0.054
(4)	0.024	0.017	0.002	0.006	0.013	0.021	0.031	0.041	0.060

NOTE: Table shows the distribution of wage effects across workers for the models in Table 6.

Table 8: Wage Effects of Broadband by Occupation IT-Use

	Full Sample, 2000–2008		Years 2003–2008	
	(1)	(2)	(3)	(4)
Broadband ×				
Intercept	0.014	0.021**	0.012	0.020*
	(0.009)	(0.008)	(0.012)	(0.012)
Computer Job	0.025***		0.032***	
	(0.009)		(0.007)	
Internet Job		0.040***		0.037***
		(0.012)		(0.014)
Computer Job	0.050***			
	(0.006)			
Internet Job		0.078***		
		(0.009)		
Worker Controls	•	•	•	•
Fixed Effects				
Establishment	•	•	•	•
Industry-Year	•	•	•	•
Job Category	•	•		
Occupation (6-digit)			•	•
Adj-R^2	.73	.73	.78	.78
Establishments	3,348	3,348	2,674	2,674
N	6,506,375	6,506,375	4,204,662	4,204,662

NOTE: Models for 2003–2008 do not include coefficients for computer or internet use because these effects are absorbed by the 6-digit occupation code fixed effect. Standard errors in parentheses are clustered by establishment.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Wage Effects of Broadband by Hierarchy Level

	(1)	(2)	(3)	(4)	(5)	(6)
Broadband ×						
Intercept	0.024***	0.024***	0.024***	0.022***	0.022***	0.023***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
Director/Manager	0.052**			0.063***		
	(0.023)			(0.021)		
Director		0.141***	0.141***		0.153***	0.153***
		(0.042)	(0.043)		(0.042)	(0.043)
Manager		0.050**	0.051**		0.061***	0.061***
		(0.023)	(0.024)		(0.021)	(0.022)
Supervisor			0.002			0.004
			(0.014)			(0.013)
Director/Manager	0.723***			0.718***		
	(0.021)			(0.019)		
Director		1.163***	1.230***		1.152***	1.220***
		(0.033)	(0.034)		(0.033)	(0.034)
Manager		0.688***	0.741***		0.683***	0.737***
		(0.021)	(0.022)		(0.019)	(0.019)
Supervisor			0.469***			0.467***
			(0.010)			(0.010)
Worker Controls	•	•	•	•	•	•
Fixed Effects						
Establishment	•	•	•	•	•	•
Year	•	•	•			
Industry-Year				•	•	•
Adj-R^2	0.70	0.70	0.71	0.71	0.71	0.72
Establishments	3,333	3,333	3,333	3,332	3,332	3,332
N	6,949,890	6,949,890	6,949,890	6,949,887	6,949,887	6,949,887

NOTE: Standard errors in parentheses are clustered by establishment.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Quantile Effects of Broadband Adoption

		Results by Hierarchy Level			
Percentile	Overall	Managers	Professionals	Technicians	Workers
10th	0.015	0.011	0.028	0.008	0.019
	(0.007)	(0.025)	(0.038)	(0.008)	(0.009)
50th	0.010	0.032	0.007	0.011	0.022
	(0.007)	(0.024)	(0.026)	(0.008)	(0.008)
90th	0.023	0.109	0.059	0.018	0.004
	(0.009)	(0.024)	(0.028)	(0.010)	(0.011)

NOTE: Standard errors in parentheses are clustered by establishment.

Table 11: Placebo Analysis of Broadband Adoption

		Placebo Summary Statistics						
Coefficient	Estimate	mean	sd	p5	p10	p50	p90	p95
Average Effect (Table 5, column 4)								
Broadband	0.022	-0.005	0.008	-0.018	-0.015	-0.004	0.006	0.009
Task Intensity (Table 6, column 2)								
Broadband ×								
Intercept	0.035	-0.001	0.009	-0.016	-0.013	-0.001	0.011	0.014
Non-routine cognitive	0.028	0.002	0.008	-0.012	-0.008	0.002	0.012	0.015
Non-routine manual	0.000	-0.001	0.004	-0.008	-0.007	-0.001	0.005	0.007
Routine cognitive	-0.027	-0.005	0.005	-0.013	-0.011	-0.005	0.002	0.003
Routine manual	0.008	-0.004	0.005	-0.012	-0.010	-0.004	0.003	0.005
Cognitive difference†	0.055	0.007	0.012	-0.013	-0.010	0.007	0.022	0.027
Occupation Computer Use (Table 8, column 1)								
Broadband ×								
Intercept	0.014	-0.006	0.009	-0.020	-0.016	-0.007	0.005	0.010
Computer Job	0.025	-0.001	0.006	-0.011	-0.009	-0.001	0.008	0.010
Occupation Internet Use (Table 8, column 2)								
Broadband ×								
Intercept	0.021	-0.006	0.008	-0.019	-0.016	-0.006	0.004	0.009
Internet Job	0.040	0.003	0.006	-0.009	-0.006	0.002	0.010	0.013
Organizational Hierarchy (Table 9, column 5)								
Broadband ×								
Intercept	0.021	-0.005	0.008	-0.019	-0.015	-0.005	0.005	0.009
Manager	0.060	-0.006	0.016	-0.031	-0.026	-0.007	0.016	0.021

NOTE: Table shows actual coefficient estimates in column 2 and summary statistics of the placebo estimates in the remaining columns.
† Cognitive difference is the difference between the coefficients for non-routine and routine cognitive tasks.

Table 12: Placebo Quantile Analysis of Broadband Adoption

		Placebo Summary Statistics						
Percentile	Estimate	mean	sd	p5	p10	p50	p90	p95
Overall Distribution (Figure 3a)								
10th	0.015	0.010	0.006	0.000	0.003	0.010	0.018	0.021
50th	0.010	0.002	0.006	-0.008	-0.006	0.002	0.010	0.012
90th	0.023	0.000	0.010	-0.016	-0.013	-0.000	0.013	0.017
Managers (Figure 3b)								
10th	0.011	-0.030	0.030	-0.077	-0.066	-0.033	0.009	0.018
50th	0.032	-0.021	0.032	-0.075	-0.059	-0.022	0.020	0.031
90th	0.109	0.038	0.032	-0.015	-0.002	0.036	0.081	0.095
Professionals (Figure 3b)								
10th	0.028	-0.017	0.040	-0.076	-0.067	-0.021	0.038	0.052
50th	0.007	-0.050	0.030	-0.100	-0.091	-0.049	-0.012	0.000
90th	0.059	-0.034	0.043	-0.101	-0.087	-0.036	0.023	0.044
Technicians (Figure 3b)								
10th	0.008	0.012	0.008	-0.002	0.001	0.011	0.023	0.026
50th	0.011	-0.015	0.007	-0.028	-0.024	-0.015	-0.006	-0.003
90th	0.018	-0.018	0.010	-0.035	-0.031	-0.018	-0.004	-0.001
Workers (Figure 3b)								
10th	0.019	0.003	0.009	-0.014	-0.009	0.003	0.015	0.018
50th	0.022	0.012	0.008	-0.003	0.001	0.012	0.021	0.023
90th	0.004	-0.001	0.012	-0.020	-0.017	-0.001	0.015	0.020

NOTE: Table shows actual coefficient estimates in column 2 and summary statistics of the placebo estimates in the remaining columns for effects on the 10th, 50th, and 90th percentiles of the wage distribution.

Table 13: Wage Effects, New vs. Existing Employees

	(1)	(2)	(3)
Broadband ×			
Intercept	0.020**	0.020**	0.023**
	(0.008)	(0.009)	(0.009)
Hiring year	0.008		
	(0.007)		
First 2 years		-0.001	
		(0.007)	
First 3 years			-0.004
			(0.008)
Worker Controls	•	•	•
Fixed Effects			
Establishment	•	•	•
Industry-Year	•	•	•
Adj-R^2	0.70	0.70	0.70
Establishments	3,348	3,348	3,348
N	6,515,673	6,515,673	6,515,673

NOTE: Standard errors in parentheses are clustered by establishment.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 14: Excluding Firms that Never Adopt Broadband

	(1)	(2)	(3)	(4)	(5)
Broadband ×					
Intercept	0.022***	0.029***	0.013	0.020**	0.021**
	(0.008)	(0.010)	(0.009)	(0.008)	(0.008)
Non-routine cognitive		0.026**			
		(0.012)			
Non-routine manual		-0.002			
		(0.007)			
Routine cognitive		-0.023**			
		(0.009)			
Routine manual		0.015*			
		(0.008)			
Computer job			0.027***		
			(0.009)		
Internet job				0.037***	
				(0.012)	
Manager					0.049*
					(0.025)
Worker Controls	•	•	•	•	•
Fixed Effects					
Establishment	•	•	•	•	•
Industry-Year	•	•	•	•	•
Adj-R^2	0.70	0.72	0.74	0.74	0.71
Establishments	1,674	1,674	1,674	1,674	1,674
N	4,235,726	4,037,168	4,230,432	4,230,432	4,235,726

Estimates in this table exclude establishments that never adopt broadband. Coefficients on variables used for interaction effects are omitted from the table to conserve space. All specifications match those in the text and main tables. Standard errors in parentheses are clustered by establishment.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 15: Restricting Sample Years Around Broadband Adoption

	(1)	(2)	(3)	(4)	(5)
Broadband ×					
Intercept	0.019** (0.009)	0.033*** (0.010)	0.012 (0.010)	0.018** (0.009)	0.017* (0.009)
Non-routine cognitive		0.026** (0.010)			
Non-routine manual		0.004 (0.005)			
Routine cognitive		-0.023*** (0.008)			
Routine manual		0.002 (0.007)			
Computer job			0.023*** (0.009)		
Internet job				0.032*** (0.012)	
Manager					0.053*** (0.020)
Worker Controls	•	•	•	•	•
Fixed Effects					
Establishment	•	•	•	•	•
Industry-Year	•	•	•	•	•
Adj-R^2	0.69	0.71	0.73	0.72	0.70
Establishments	3,336	3,336	3,336	3,336	3,336
N	5,553,253	5,304,446	5,544,903	5,544,903	5,553,253

Estimates in this table limit the sample to at most 4 years before and after broadband adoption. Coefficients on variables used for interaction effects are omitted from the table to conserve space. All specifications match those in the text and main tables. Standard errors in parentheses are clustered by establishment.

* $p < .10$, ** $p < .05$, *** $p < .01$