The Wage and Inequality Impacts of Broadband Internet

Christopher W. Poliquin

University of California, Los Angeles

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Abstract

Who benefits from technology adoption in the workplace? To explore, I combine worker-level wage data with information on broadband adoption by Brazilian firms to estimate the effects of broadband on wages. Overall, wages increase 2.3 percent following broadband adoption. Consistent with the theory of biased technological change, wages increase the most for workers engaged in non-routine cognitive tasks and occupations that require use of information technology. There is no effect of broadband adoption on wages for either routine or non-routine manual tasks. Additionally, I estimate the effect of broadband on selected quantiles of the within-firm wage distribution and find evidence that within-firm wage inequality increases following broadband adoption. Both new hires and the firm's existing employees benefit from broadband adoption, which indicates that broadband's effects are not driven only by better recruitment of new employees.

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Email: `chris.poliquin@anderson.ucla.edu`

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1 Introduction

Who benefits from technology adoption in the workplace? Technology can substitute for some workers while complementing others. Specifically, the "task approach" to labor markets highlights the potential for digital technologies to substitute for workers in performing routine tasks, while complementing workers in non-routine tasks (Autor et al., 2003). To date, empirical work on this hypothesis has largely relied on industry-, region-, or to a lesser extent, firm-level data. In contrast, this paper uses worker-level wage data in conjunction with firm-level information on technology use over time. Specifically, I study how broadband internet technology affects the wages of individual workers *within* firms.

I find that wages increase 2.3 percent following firm broadband adoption, but the effect of broadband is heterogeneous. Regressions of wages on the task profile of jobs suggest that broadband complements employees performing non-routine cognitive tasks, while substituting for workers in routine cognitive tasks. Intuitively, both routine and non-routine manual tasks are unaffected by broadband. Additionally, I find that increases in wages following broadband adoption are largest for workers in occupations that require the use of information technology.

Differences in the returns to broadband across occupations and tasks have implications for within-firm wage inequality. I examine changes to the entire wage distribution within firms following broadband adoption using a grouped quantile regression estimator (Chetverikov et al., 2016). Wage increases following broadband are concentrated in the right tail of the wage distribution; in other words, within-firm wage inequality increases after broadband adoption. This result contributes to a literature that emphasizes the role of firms in determining pay inequality (e.g. Cobb, 2016; Gartenberg and Wulf, 2017b; Nickerson and Zenger, 2008), and provides the first direct evidence connecting adoption and use of advanced information technology to a widening pay gap *within* organizations.

As evidence of broadband enhancing the productivity of existing workers, rather than only improving the recruitment of new workers, I show that wages increase for both new hires and existing employees following broadband adoption. Furthermore, firm directors—who are most likely to also be firm owners in my sample—appear to capture large rents from the introduction of broadband, a pattern consistent with increased firm productivity post-adoption.

The analysis combines an employer-employee matched dataset from Brazil with firm-level data on technology use over time. By linking information on which firms use broadband with data on their individual workers, I can estimate the effect of broadband within firms over time. Additionally, I can examine changes in the wages of individual workers while controlling for worker characteristics and unobserved firm heterogeneity.

This paper is among the first to combine within-firm variation on technology use with large-sample microdata on the wages and characteristics of individual workers. While other research has examined the impact of internet technology on wages, prior studies have not observed changes in the technology used at individual firms over time. Recent research on how the internet effects workers and firms in Brazil (Almeida et al., 2017; Dutz et al., 2017), Africa (Hjort and Poulsen, 2017), Norway (Akerman et al., 2015), Canada (Ivus and Boland, 2015), and the United States (Forman et al., 2012; Gillett et al., 2006; Kolko, 2012) relies on geographic variation in internet availability and/or cross-sectional variation in firm adoption. In contrast, I build on these studies by observing the same firm and workers before and after the adoption of broadband. The results of this paper are consistent with prior work, which shows broadband has heterogeneous effects and substitutes for workers engaged in routine tasks while complementing workers engaged in non-routine tasks.

Broadband technology is especially worthy of study because of the internet's pervasiveness and policymakers' interest in public investments in broadband infrastructure. Nearly 50 percent of people worldwide now access the internet. The transformation of the internet 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 operations and jobs.

Although a number of studies suggest that broadband, and internet access generally, is a skill-biased technological change, few if any provide concrete examples of how or why this might be the case. The next section provides anecdotal evidence from interviews with Brazilian managers suggesting that broadband use in firms can assist workers with IT-intensive and non-routine cognitive tasks while substituting for workers in performing routine cognitive tasks.

2 Anecdotal Evidence

This section provides examples, through interviews with managers in Brazilian firms, of how broadband can affect firm operations. 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.

Managers I interviewed described using broadband to facilitate information exchange both within and between firms and customers. 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."

The 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 IT-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."

A provider of medical imaging services explained using broadband to automate appointment scheduling, therefore eliminating the routine task of finding open dates. At the same time, this firm leveraged broadband to unify databases across multiple work sites in a single location so that important documents could be shared and accessed from anywhere. This made it easier for doctors to access patient medical records across facilities.

A manufacturer of bottled water reported using broadband to connect its machines to the company that supplied them so that their performance could be monitored remotely. This change obviated the need for someone who could monitor the machine's controls, eliminating the routine task of documenting and recording information.

In addition to these examples, managers reported using broadband to stay in closer contact with their customers, research competitors, and communicate with subordinates.

3 Data

The data used in this study are richer than data used in prior studies of broadband adoption because they include information on individual workers and their employers over time. This allows me to examine how wages change for different types of workers following firm adoption of broadband.

Data on individual workers come from the *Relação Anual de Informações Sociais* (RAIS) for the years 2000 through 2009. RAIS is an establishment-employee matched survey of all employers in Brazil's formal economy conducted annually by 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 (but not hours actually worked).

I combine the employer-employee matched data from RAIS with firm-level data on broadband adoption from the Latin American version of the Ci Technology Database (CiTDB) from Aberdeen Group.[1] 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). CiTDB contains information on communication technologies used by the firm (e.g. xDSL, T1, etc.), which I use to measure broadband adoption. 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). I limit my study to manufacturing firms—which is the largest group of businesses in the data—with technology adoption information in Harte Hanks and wages in RAIS so that analyses of the task content of jobs and occupational hierarchy can be more easily interpreted.

[Figure 1 about here.]

Figure 1 shows that broadband use increased substantially from 2000 to 2009; fewer than 20 percent of the sample firms used broadband in 2000, but more than 70 percent had a broadband connection by 2009. Note that these numbers are not necessarily representative of all Brazilian manufacturing firms. The firms surveyed by Harte Hanks—my source of technology data—are larger than the typical firm in Brazil.

To examine how the effects of broadband vary for different types of workers, I use

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

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[2] 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 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 1 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 1 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

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

U.S. codes using a crosswalk developed by Nogueira Maciente (2019).[3] 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 2003–2009) using the official crosswalk. I then separately analyze both the full sample period from 2000–2009 as well as the shorter period from 2003–2009 to ensure my results are not driven by quirks of the conversion process.

Additionally, 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 four layers:

1. Directors (e.g. Chief Executive Officer, Chief Financial Officer)
2. Managers (e.g. Sales Manager, Branch Manager)
3. Supervisor (e.g. Foreman, Logistics Supervisor)
4. 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 2 shows the mean and selected percentiles of the wage distribution by layer. Directors and managers have higher wages than supervisors, who have higher wages than workers (at all percentiles).

[Table 2 about here.]

[3]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.

4 Methodology

I use a staggered difference-in-differences research design that identifies the effect of broadband adoption on wages by comparing firms that did and did not adopt broadband over the ten-year period between 2000 and 2009.

The main models of interest examine the effect of broadband adoption on workers, allowing for the effect of broadband to differ by occupation:

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

where w_{ijht} is the real wage of worker i at firm j in year t. D_{jt} is an indicator variable for broadband use by firm j and K_{it} is a vector of occupation attributes (e.g. task measures, IT-intensity) 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 depends on features of the jobs that workers perform. 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.[4] Some specifications also include log employment, L_{jt}, to control for the possibility that larger firms 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 use employment as the dependent variable in other analyses and omit it from most models. The model includes both firm (α_j) and industry-year ($\lambda_{\kappa(j)t}$, where $\kappa(j)$ is the industry of firm j) fixed effects that control for unobserved firm heterogeneity and annual shocks that affect all workers within an industry equally.[5].

[4]The data do not include actual hours worked, but do include hours in the labor contract. Full-time work in Brazil is 44 hours per week.

[5]I estimate the model using the estimator from Correia (2016).

[Table 3 about here.]

A key assumption of the above model is that the trend in wages for firms that adopt broadband was parallel to the trend at other firms prior to adoption. I present support for this assumption in section 6 and conduct several robustness checks to ensure my results are not driven by violations of the parallel trends assumption.

Combining employer-employee matched data with information on technology use over time allows me to examine how the entire wage distribution within firms changes following broadband adoption. To do so, I implement the grouped quantile regression approach from Chetverikov et al. (2016). 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 firm j in year t, D_{jt} is an indicator for firm broadband adoption, and α_j and $\lambda_{\kappa(j)t}$ are firm and industry-year fixed effects.

The grouped quantile approach allows me to estimate how broadband adoption affects inequality within firms. Greater effects of broadband in the upper quantiles of the wage distribution than in lower quantiles imply that inequality within firms increases following broadband adoption.

In addition to studying the effect of broadband on wages, I also examine how employment changes at the firm level following broadband adoption:

$$L_{jt} = \beta D_{jt} + \alpha_j + \lambda_{\kappa(j)t} + \epsilon_{jt} \tag{3}$$

Table 3 presents summary statistics of variables used in the analyses. Just over half of observations are for people working in firms that use broadband.

5 Results

5.1 Wage Effects

Overall, wages increase 2.3 percent following firm adoption of broadband. Table 4 shows the effect of broadband adoption without distinguishing between occupations or types of employees. The results in columns 2–3 include firm and year fixed effects, while columns 4–5 include firm 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 firm size. The increase in wages following broadband adoption, therefore, is not explained by bigger, growing firms paying both higher wages and simultaneously choosing to adopt broadband.

[Table 4 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), in which case estimates from the sample of adopters will be greater than the effect of introducing other firms to broadband. 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 impacts 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. Second, the problem of firms selecting into broadband use is alleviated by the ten-year sample period. Figure 1 shows that most firms in the sample eventually adopt broadband. Third, I examine wage trends prior to broadband adoption. Figure 2 shows coefficient estimates from a modified version of the model in column 4 of Table 4 that includes separate dummy variables for years before and after adoption. These single-year estimates are imprecise, but show that the largest wage increases happen in the years following broadband adoption. There are no statistically significant "effects" of broadband on wages prior to adoption.

I further examine the robustness of the results in section 6 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, selection effects, or (omitted) variables that could have affected wages several years after broadband adoption.

The effect of broadband is heterogeneous; 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 5 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 2003–2009 because the occupation coding system changed in 2003 (see section 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 5 about here.]

Table 5 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 6 about here.]

The use of four, continuous task measures interacted with broadband complicates interpretation of the results in Table 5. Table 6 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 5 and the task intensities of the worker's occupation to calculate the hypothetical impact of broadband for that worker. I then calculate the distribution of these wage effects across all workers. The results in Table 6 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 wage losses in the left tail.

Overall, the broadband/task interaction effects of Table 5 are consistent with the routinization hypothesis that computer technology complements and increases demand for non-routine tasks while substituting for routine tasks (Autor et al., 2003). In the case of broadband, this pattern is pronounced for cognitive tasks, but not present for manual tasks.

To further examine the claim that broadband complements certain workers and drives the observed wage increases, I interact broadband adoption with dummies for on-the-job use of information technology. Specifically, I measure whether an occupation requires use of a computer 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."[6] Additionally, I identify every tool that mentions "internet", "intranet", or "extranet" and classify these as "internet jobs."

[Table 7 about here.]

Table 7 shows that the impact of broadband on individuals' wages is greatest for workers in occupations that commonly require using a computer or the internet. The baseline impacts of broadband adoption range from roughly 1–2 percent, but workers in occupations that use information technology see gains of 4–5.5 percent. The wage benefits of broadband adoption are therefore (not surprisingly) greatest for workers most likely to use computers or the internet as part of their job. Additionally, 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 5–7, 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 analysis of information technology use in Table 7 is split into two time periods because the occupation coding scheme changed in 2003 and the measures of on-the-job tool

[6] For example, jobs whose tools include "computer", "microcomputer", or "computer software" are labeled "computer jobs."

use were developed for the later (2003–2009) scheme (see section 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 IT-intensive jobs likely differ on dimensions other than computer and internet use. To show that the results also hold for the longer (2000–2009) 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 5 broad job categories (director, manager, supervisor, professional, and worker) and see similar results.[7]

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.[8] A possible explanation for the 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.

5.2 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 only by firms

[7]Including the 6-digit occupation fixed effect is not possible for the 2000–2009 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.

[8]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).

recruiting better workers post-adoption. Table 8 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 firm. The results show that newly hired employees do not earn an additional wage premium from broadband adoption over that earned by existing employees.

[Table 8 about here.]

5.3 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. Columns 1 and 4 of Table 9 show that directors and managers earn 8–9 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 18–19 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 an ownership stake in the firm than if the firms were public. The wage increases for directors are 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 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 distribution of wages within firms.

Figure 3 plots the effect of broadband on selected quantiles of the wage distribution. Although the estimates for the individual quantiles are imprecise, the pattern of point estimates in Figure 3 shows 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.]

Research on organizational hierarchy and pay suggests that communication technology widens the gap between hierarchical layers of firms because cheaper communications allow firms to centralize decision-making functions in fewer employees, who occupy the top of the organizational hierarchy (Garicano, 2000; Garicano and Rossi-Hansberg, 2006). This same research also suggests that information technology has opposite effects: easier access to information increases the level of knowledge used in production and the pay of lower-level employees. Broadband internet cannot be neatly classified as either a communication or information technology; it's both (see section 2), and the predictions of this literature would therefore depend on the highly specific ways that individual firms use broadband. The results of this study, however, would be consistent with either broadband reducing communication costs to the benefit of upper-level employees (see Table 9) or reducing information acquisition costs for specific occupations (e.g. jobs that accommodate computer use—see Table 7) in the upper-end of the wage distribution.

Broadband's effect in widening the within-firm wage distribution is noteworthy for the literatures on vertical pay comparisons within firms (e.g. Gartenberg and Wulf, 2017a,b; Kacperczyk and Balachandran, 2018), the antecedents of compensation policies (e.g. Chin and Semadeni, 2017; Fredrickson et al., 2010), and the role of firms in determining pay inequality (e.g. Cobb, 2016). This paper provides the first direct evidence connecting adoption and use of advanced information technology to widening pay gaps within organizations. Furthermore, this paper provides estimates of broadband's effect across the entire wage distribution; existing research on pay dispersion is largely focused on top-management teams and key employees.

Prior work suggests that pay inequality can have psychological costs (Larkin et al., 2012), and can negatively impact performance (Fredrickson et al., 2010; Siegel and Hambrick, 2005). Unfortunately, I do not have data to assess either the first order effect of broadband on performance or any second order effects operating through employee motivation. I also lack data on performance-linked compensation that would allow me to examine how different components of pay change in response to technology adoption.

5.4 Employment Effects

[Table 10 about here.]

Broadband has positive effects on firm-level employment. Column 1 of Table 10 indicates that employment increases roughly 5.4 percent following broadband adoption. Columns 2 and 3 show separate regressions for managerial and non-managerial employees respectively. These estimates are not statistically different from zero at conventional significance levels, and the point estimates do not suggest different employment effects for workers and managers following broadband adoption. Columns 4–6, which include industry-year fixed effects instead of just year fixed effects, show slightly larger estimates. Column 4 indicates that employment increases about 7 percent following broadband adoption, and columns 5–6 again suggest that the effect is similar for manages and non-managers.

6 Robustness Checks and Alternative Explanations

This section presents several robustness checks related to the difference-in-differences estimation strategy. Figure 2 shows that pre-trends in average wages are roughly similar for firms that do and do not adopt broadband, but there is some (not statistically significant) evidence of an effect in the year prior to adoption. In this section, I conduct several supplementary analyses to further examine the parallel trends assumption as well as the robustness of the results.

6.1 Placebo Analyses and Parallel Trends

[Table 11 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 4—shows a mean placebo estimate of -0.003 and an actual estimate of the coefficient on broadband (0.023) that exceeds more than 95 percent of the placebo estimates.

Results for placebo analyses of broadband interacted with occupation tasks (Table 5), use of information technology (Table 7), 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.

6.2 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 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.

6.3 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 impact on wages soon after broadband adoption. To further support the claim that broadband increases wages, however, I re-estimate my models 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.

7 Conclusion

The results of this study contribute to research on the wage and employment 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, 2017), 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.

I combine data on firm adoption of broadband technology over time with data on individual workers to estimate the effects of broadband on wages and employment. Overall, wages increase 2.3 percent following broadband adoption, but the effects are heterogeneous. Consistent with the theory of skill-biased technological change, wages increase the most for workers engaged in non-routine cognitive tasks. Returns for routine cognitive tasks are negative, and intuitively, the effect of broadband does not vary in the intensity of either routine or non-routine manual tasks. Similarly, the wage effects of broadband are largest for workers in occupations that require use of computers or the internet, even after controlling for other unobserved attributes of these occupations with six-digit occupation fixed-effects. Quantile regressions measuring the effect of broadband on the full wage distribution suggest that broadband increases within-firm wage inequality.

Additionally, I am able to compare the returns of broadband adoption for new and existing employees. I find that both new and existing employees benefit from broadband adoption, which suggests the effect of broadband on wages is not solely the result of recruiting better employees post-adoption. Overall employment increases 5–7 percent following broadband adoption.

These results are useful for policymakers evaluating the potential impacts of public investment in broadband infrastructure. Such investments are often predicated on the hypothesis that high-speed internet spurs economic and wage growth despite limited research on this topic. I show that workers do indeed benefit on average by earning higher wages following broadband adoption. Workers, however, do not equally share the gains from broadband adoption; those engaged in higher paid occupations that require IT-use and are intensive in non-routine cognitive tasks experience larger gains from adoption than workers in other occupations.

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 5. 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.[9]

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

[9]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 (2000–2009). 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.

Coefficient estimates based only off the sample of adopting firms, however, are similar in magnitude to those from the full sample (Table 12). This suggests that the results are not driven by different wage trends in firms that do and do not adopt broadband technology.

[Table 12 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 13). This pattern, combined with the fact that wage impacts 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 13 about here.]

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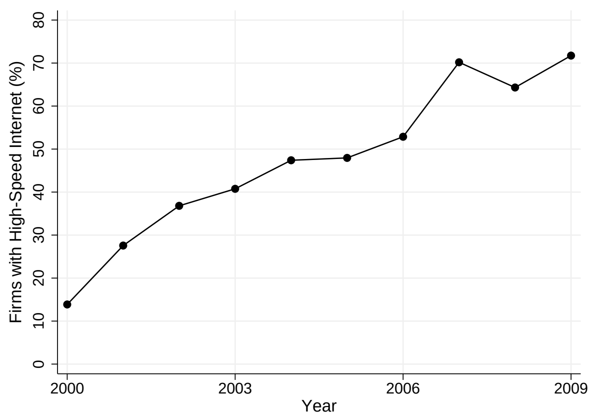
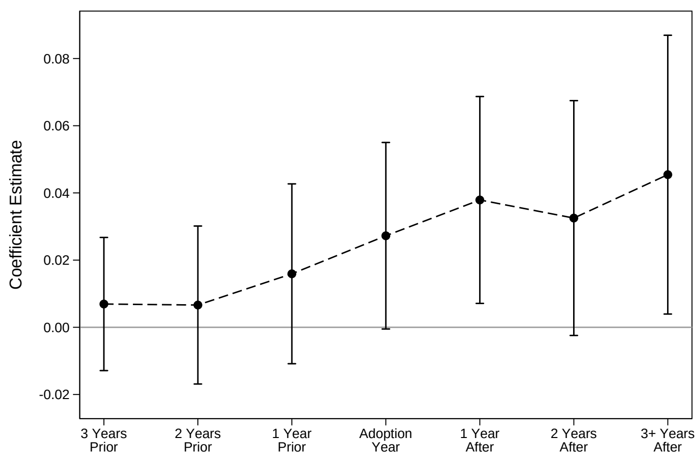
Figure 1: Adoption of High-Speed Internet



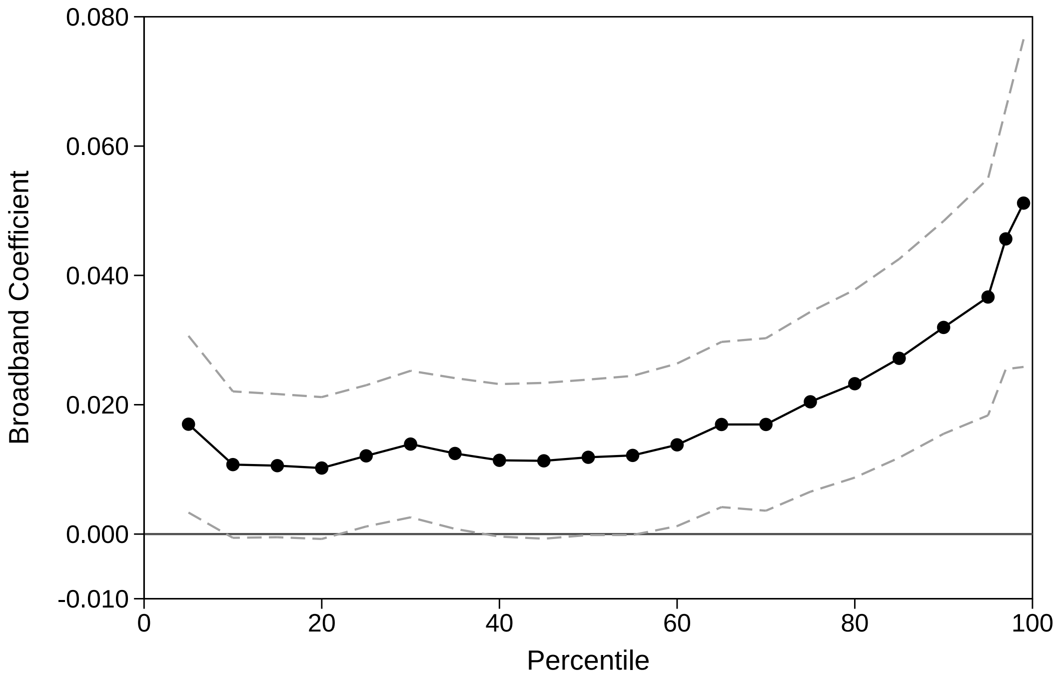
Note:

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



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

Table 1: 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	-0.20	1.32	1.43
Routine manual	0.84	0.93	-0.93	-0.45	1.00	2.07	2.07

NOTE: Table shows distribution of occupation task measures across workers.

Table 2: Wage Distribution by Hierarchy Level

	Director	Manager	Supervisor	Worker
mean	18,085	8,679	3,763	1,476
p5	1,593	1,053	735	391
p10	3,030	1,692	984	468
p25	7,573	3,458	1,674	636
p50	16,617	7,144	2,953	961
p75	26,403	11,767	4,979	1,648
p90	35,531	17,166	7,365	2,937
p95	40,745	21,779	9,145	4,222

NOTE: Wages are mean monthly wage in 2008 reais.

Table 3: Summary Statistics

	mean	sd	p5	p10	p50	p90	p95
High-speed internet	0.52	0.50	0	0	1	1	1
Log wage	7.05	0.81	6.0	6.2	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	60.45	70.92	1.9	3.4	32.7	161.9	211.9
Age	33.11	10.10	20.0	21.0	32.0	47.0	52.0
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	0.28	0	0	0	0	1
Some Middle School	0.14	0.35	0	0	0	1	1
Middle School	0.15	0.35	0	0	0	1	1
Some High School	0.10	0.31	0	0	0	1	1
High School	0.31	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: Log wages are log of mean monthly wage in 2008 reais.

Table 4: Wage Effects of Broadband

	(1)	(2)	(3)	(4)	(5)
Broadband	0.034***	0.026***	0.026***	0.023***	0.023***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Log Employees			0.015**		-0.007
			(0.007)		(0.008)
Worker Controls		•	•	•	•
Fixed Effects					
Firm	•	•	•	•	•
Year	•	•	•		
Industry-Year				•	•
Adj-R^2	0.45	0.69	0.69	0.69	0.69
Firms	3,333	3,333	3,333	3,332	3,332
N	6,949,890	6,949,890	6,949,890	6,949,887	6,949,887

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

Table 5: Wage Effects of Broadband by Tasks

	Full Sample, 2000–2009		Years 2003–2009	
	(1)	(2)	(3)	(4)
Broadband ×				
Intercept	0.030***	0.034***	0.030**	0.033***
	(0.010)	(0.010)	(0.013)	(0.013)
Non-routine cognitive	0.034***	0.028**	0.025*	0.022*
	(0.011)	(0.011)	(0.013)	(0.013)
Non-routine manual	0.008	0.000	0.000	-0.005
	(0.007)	(0.006)	(0.007)	(0.007)
Routine cognitive	-0.033***	-0.028***	-0.027***	-0.024**
	(0.009)	(0.009)	(0.010)	(0.011)
Routine manual	0.013*	0.010	0.005	0.005
	(0.007)	(0.007)	(0.009)	(0.009)
Non-routine cognitive	0.189***	0.194***	0.199***	0.200***
	(0.009)	(0.008)	(0.010)	(0.010)
Non-routine manual	-0.066***	-0.063***	-0.062***	-0.059***
	(0.005)	(0.004)	(0.005)	(0.005)
Routine cognitive	-0.039***	-0.041***	-0.047***	-0.049***
	(0.007)	(0.006)	(0.008)	(0.009)
Routine manual	-0.044***	-0.043***	-0.035***	-0.035***
	(0.005)	(0.006)	(0.008)	(0.008)
Worker Controls	•	•	•	•
Fixed Effects				
Firm	•	•	•	•
Year	•		•	
Industry-Year		•		•
Adj-R^2	0.71	0.72	0.73	0.73
Firms	3,332	3,332	2,661	2,661
N	6,635,321	6,635,321	4,419,468	4,419,468

NOTE: Standard errors in parentheses are clustered by firm. 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 2003–2009 (columns 3 and 4).
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Summary of Wage Effects of Broadband by Tasks

Model	mean	sd	p5	p10	p25	p50	p75	p90	p95
(1)	0.028	0.026	-0.022	-0.001	0.015	0.029	0.043	0.067	0.074
(2)	0.029	0.020	-0.006	0.005	0.019	0.030	0.038	0.059	0.060
(3)	0.022	0.020	-0.007	-0.001	0.011	0.023	0.029	0.049	0.055
(4)	0.025	0.017	0.002	0.003	0.014	0.025	0.032	0.042	0.059

NOTE: Table shows the distribution of wage effects across workers for the models in Table 5.

Table 7: Wage Effects of Broadband by Occupation IT-Use

	Full Sample, 2000–2009		Years 2003–2009	
	(1)	(2)	(3)	(4)
Broadband ×				
Intercept	0.015*	0.022***	0.013	0.021**
	(0.009)	(0.008)	(0.011)	(0.011)
Computer Job	0.026***		0.030***	
	(0.009)		(0.007)	
Internet Job		0.038***		0.035**
		(0.012)		(0.014)
Computer Job	0.048***			
	(0.007)			
Internet Job		0.092***		
		(0.009)		
Worker Controls	•	•	•	•
Fixed Effects				
Firm	•	•	•	•
Industry-Year	•	•	•	•
Job Category	•	•		
Occupation (6-digit)			•	•
Adj-R^2	0.72	0.72	0.78	0.78
Firms	3,332	3,332	2,662	2,662
N	6,940,676	6,940,676	4,647,270	4,647,270

NOTE: Models for 2003–2009 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 firm.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Wage Effects, New vs. Existing Employees

	(1)	(2)	(3)	(4)	(5)	(6)
Broadband ×						
Intercept	0.023***	0.023***	0.024***	0.021***	0.020**	0.022**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
Hiring year	0.009			0.008		
	(0.007)			(0.007)		
First 2 years		0.003			0.001	
		(0.008)			(0.007)	
First 3 years			0.001			-0.002
			(0.008)			(0.008)
Hiring year	-0.136***			-0.136***		
	(0.005)			(0.005)		
First 2 years		-0.155***			-0.154***	
		(0.005)			(0.005)	
First 3 years			-0.152***			-0.151***
			(0.006)			(0.005)
Worker Controls	•	•	•	•	•	•
Fixed Effects						
Firm	•	•	•	•	•	•
Year	•	•	•			
Industry-Year				•	•	•
Adj-R^2	0.69	0.69	0.69	0.69	0.70	0.70
Firms	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 firm.
* $p < .10$, ** $p < .05$, *** $p < .01$

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						
Firm	•	•	•	•	•	•
Year	•	•	•			
Industry-Year				•	•	•
Adj-R^2	0.70	0.70	0.71	0.71	0.71	0.72
Firms	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 firm.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 10: Employment Effects of Broadband

	Total	Managers	Workers	Total	Managers	Workers
	(1)	(2)	(3)	(4)	(5)	(6)
Broadband	0.053**	0.044*	0.040	0.071***	0.054**	0.058**
	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)	(0.026)
Fixed Effects						
Firm	•	•	•	•	•	•
Year	•	•	•			
Industry-Year				•	•	•
Adj-R^2	0.84	0.79	0.85	0.84	0.81	0.76
Firms	3,026	2,722	3,023	2,990	2,990	2,990
N	17,722	15,348	17,696	17,310	17,310	17,310

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

Table 11: Placebo Analysis of Broadband Adoption

		Placebo Summary Statistics						
Coefficient	Estimate	mean	sd	p5	p10	p50	p90	p95
Average Effect (Table 4, column 4)								
Broadband	0.023	-0.003	0.008	-0.015	-0.013	-0.003	0.008	0.011
Task Intensity (Table 5, column 2)								
Broadband ×								
Intercept	0.034	0.000	0.008	-0.013	-0.010	-0.000	0.010	0.014
Non-routine cognitive	0.028	0.000	0.007	-0.011	-0.010	0.000	0.010	0.013
Non-routine manual	0.000	-0.001	0.004	-0.008	-0.007	-0.001	0.004	0.006
Routine cognitive	-0.028	-0.004	0.005	-0.013	-0.011	-0.004	0.001	0.003
Routine manual	0.010	-0.004	0.005	-0.012	-0.010	-0.004	0.003	0.004
Cognitive difference†	0.056	0.005	0.011	-0.012	-0.010	0.005	0.020	0.023
Occupation Computer Use (Table 7, column 1)								
Broadband ×								
Intercept	0.015	-0.001	0.008	-0.014	-0.012	-0.002	0.009	0.012
Computer Job	0.026	-0.006	0.007	-0.017	-0.015	-0.006	0.003	0.005
Occupation Internet Use (Table 7, column 2)								
Broadband ×								
Intercept	0.022	-0.003	0.008	-0.015	-0.013	-0.003	0.008	0.010
Internet Job	0.038	0.000	0.007	-0.010	-0.008	-0.001	0.009	0.012
Organizational Hierarchy (Table 9, column 5)								
Broadband ×								
Intercept	0.022	-0.003	0.007	-0.015	-0.013	-0.004	0.008	0.010
Manager	0.063	-0.008	0.014	-0.028	-0.025	-0.010	0.012	0.016

NOTE: Table shows actual coefficient estimates in column 2 and summary statistics of the placebo estimates in the remaining columns.

Table 12: Excluding Firms that Never Adopt Broadband

	(1)	(2)	(3)	(4)	(5)
Broadband ×					
Intercept	0.023***	0.029***	0.014	0.023***	0.022***
	(0.008)	(0.010)	(0.009)	(0.008)	(0.008)
Non-routine cognitive		0.027**			
		(0.012)			
Non-routine manual		-0.001			
		(0.007)			
Routine cognitive		-0.025***			
		(0.009)			
Routine manual		0.017**			
		(0.008)			
Computer job			0.030***		
			(0.010)		
Internet job				0.036***	
				(0.012)	
Manager					0.054**
					(0.026)
Worker Controls	•	•	•	•	•
Fixed Effects					
Firm	•	•	•	•	•
Industry-Year	•	•	•	•	•
Adj-R^2	0.70	0.72	0.73	0.73	0.71
Firms	1,669	1,669	1,669	1,669	1,669
N	4,667,143	4,446,852	4,661,891	4,661,891	4,667,143

NOTE: Estimates in this table exclude firms 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 firm.
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 13: Restricting Sample Years Around Broadband Adoption

	(1)	(2)	(3)	(4)	(5)
Broadband ×					
Intercept	0.019**	0.030***	0.012	0.018**	0.018**
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
Non-routine cognitive		0.024**			
		(0.010)			
Non-routine manual		0.004			
		(0.005)			
Routine cognitive		-0.024***			
		(0.008)			
Routine manual		0.004			
		(0.007)			
Computer job			0.022**		
			(0.009)		
Internet job				0.029**	
				(0.012)	
Manager					0.050**
					(0.020)
Worker Controls	•	•	•	•	•
Fixed Effects					
Firm	•	•	•	•	•
Year					
Industry-Year	•	•	•	•	•
Adj-R^2	0.69	0.72	0.72	0.72	0.70
Firms	3,321	3,321	3,321	3,321	3,321
N	5,761,369	5,503,856	5,753,099	5,753,099	5,761,369

NOTE: 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 firm.

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