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THE SKILL COMPLEMENTARITY OF BROADBAND INTERNET

Anders Akerman
Ingvil Gaarder
Magne Mogstad

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ABSTRACT

Does adoption of broadband internet in firms enhance labor productivity and increase wages? And is this technological change skill biased or factor neutral? We exploit rich Norwegian data to answer these questions. A public program with limited funding rolled out broadband access points, and provides plausibly exogenous variation in the availability and adoption of broadband internet in firms. Our results suggest that broadband internet improves (worsens) the labor outcomes and productivity of skilled (unskilled) workers. We explore several possible explanations for the skill complementarity of broadband internet. We find suggestive evidence that broadband adoption in firms complements skilled workers in executing nonroutine abstract tasks, and substitutes for unskilled workers in performing routine tasks. Taken together, our findings have important implications for the ongoing policy debate over government investment in broadband infrastructure to encourage productivity and wage growth.

Anders Akerman
Stockholm University
Department of Economics
anders.akerman@gmail.com

Ingvil Gaarder
University of Chicago
Department of Economics
ingvil.gaarder@gmail.com

Magne Mogstad
Department of Economics
University of Chicago
1126 East 59th Street
Chicago, IL 60637
and NBER
magne.mogstad@gmail.com

1 Introduction

Economists and policymakers are keenly interested in understanding the productivity and labor market effects of the advancements in information and communication technology (ICT). Many have argued that these technological changes were behind the resurgence in U.S. productivity growth since the late 1990s, and that investments in ICT are important in explaining labor productivity patterns across multiple industries and countries.[1] Recently, policymakers have pointed to broadband internet as a key productivity enhancing factor, calling for public funding to roll out broadband infrastructure. While government agencies are projecting broadband penetration rates to be important for productivity and job creation,[2] there is little scientific evidence to substantiate these claims.[3]

In this paper, we examine how broadband internet affects the labor outcomes and productivity of different types of workers. Our context is the adoption of broadband internet in Norwegian firms over the period 2001-2007. Norway is a small open economy with segmented local labor markets. Our analysis employs several data sources that we can link through unique firm and individual identifiers. This gives us information over time and across areas on individuals' wages and employment status as well as on firms' use of input factors, adoption of broadband internet, and output.

As a source of exogenous variation in broadband availability, we follow Bhuller, Havnes, Leuven, and Mogstad (2013) in exploiting a public program aimed at ensuring broadband access at a reasonable price to all households throughout the country.[4] Because of limited funding, access to broadband was progressively rolled out, so that the necessary infrastructure (access points) was established in different municipalities at different times. Conditional on year and municipality fixed effects, we argue the spatial and temporal variation in the availability of broadband across municipalities is plausibly exogenous. Our identification strategy is motivated by two features of the broadband program. First, most of the supply and demand factors tend to vary little over time. Second, the timing of the roll-out across areas is unlikely to co-vary with the key correlates of productivity and labor outcomes. We demonstrate that the data is consistent with these program features, and

[1] The evidence is reviewed in Draca, Sadun, and Van Reenen (2007), Oliner, Sichel, and Stiroh (2007), Jorgenson, Ho, and Stiroh (2008), and Syverson (2011). See also Bloom, Sadun, and Van Reenen (2012).

[2] In 2008, the U.S. Commissioner of Federal Communications Commission stated that "Affordable broadband would quickly add \$500 billion to the U.S. Economy and create 1.2 million jobs". Projections from the U.S. Bureau of Economic Analysis suggest that for every \$1 invested in broadband, the economy benefits nearly \$3.

[3] A notable example of research on this topic is Czernich, Falck, Kretschmer, and Woessmann (2011), who find positive association between broadband penetration and economic growth across OECD countries over time. Another example is Forman, Goldfarb, and Greenstein (2012), showing that internet investments correlate with wage and employment growth in some but not all U.S. counties. Atasoy (2013) shows the correlation is stronger in counties where a larger share of the population has a college degree, pointing to a skill complementarity of broadband internet.

[4] Bhuller, Havnes, Leuven, and Mogstad (2013) use the roll-out of broadband internet to study how internet use affects sex crimes.

further challenge our identification strategy in a number of ways, finding little cause for worry.

We begin by estimating the intention-to-treat effects of the increased availability of broadband internet on the labor outcomes and productivity of different types of workers. We find two pieces of evidence that suggest skill complementarity of broadband internet. On the worker side, we find that wages and employment of (un)skilled individuals increases (decreases) with broadband availability.[5] On the firm side, we find that increased availability of broadband internet is associated with a substantial increase (decrease) in the output elasticity of (un)skilled labor. A comparison of the changes in output elasticities and labor outcomes suggest that firms earn substantial rent from increased availability of broadband internet, at least in the short run.

Using the rich Norwegian data, we explore several possible channels through which increased availability of broadband internet may affect labor outcomes and productivity. We find evidence against the hypothesis that our findings reflect changes in the demand for goods due to the expansion of broadband internet. Our data is also at odds with broadband adoption coinciding with general technical upgrading in firms. Another possible mechanism receiving little support in data is that our findings are driven by changes in labor productivity and wages in firms directly affected by the expansion of broadband access, such as telecom firms or IT consultancy companies.

Instead, we find suggestive evidence that increased availability of broadband internet affects labor outcomes and productivity primarily through broadband adoption in firms. If that is the case, the plausibly exogenous variation in broadband availability may serve as an instrument for broadband adoption in firms. This allows us to estimate production functions where firms can change their technology by adopting broadband internet. We find that broadband adoption in firms is a skill biased technological change, shifting how factor inputs are transformed into output. In particular, this technological change increases the marginal productivity of skilled workers, and lowers the marginal productivity of unskilled workers.

To better understand the skill complementarity of broadband internet, we pursue a task based approach to skill biased technological change. Autor, Levy, and Murnane (2003) argue that ICT substitutes for workers in performing routine tasks – more amenable to automatization – and complements workers in executing problem-solving, complex communication, and information-intensive tasks (ofted called “nonroutine abstract tasks”).[6] A

[5]Throughout the paper, we follow the literature by referring to education and skills interchangeably; thus skilled refers to highly educated and unskilled refers to those with lower levels of education.

[6]See also Autor, Katz and Kearney (2006, 2008), Goos and Manning (2007), Black and Spitz-Oener (2010), Firpo, Fortin, and Lemieux (2011), Acemoglu and Autor (2011), Autor and Dorn (2013), and Michaels, Natraj, and Van Reenen (2014). A related literature argues that ICT changes workplace organization and practices, by increasing skill requirements, worker autonomy and management’s ability to monitor workers (see e.g. Caroli and Van Reenen, 2001; Bresnahan, Brynjolfsson, and Hitt, 2002; Brynjolfsson and Hitt, 2003; Bloom, Garicano, Sadun, and Van Reenen, 2009).

necessary condition for a task based explanation of the skill complementarity of broadband internet is that workers of different educational background actually cluster disproportionately in occupations that require different tasks. In our data, we find that skilled workers are over-represented in occupations that are pervasive at nonroutine abstract tasks, whereas unskilled workers are often in occupations that involve routine tasks. Motivated by these differences, we estimate wage regressions which include interactions between broadband internet and the tasks performed in jobs in addition to the educational credentials of workers performing those jobs. The estimates suggest an important channel behind the skill bias of broadband internet is that it complements non-routine abstract tasks but substitutes for routine tasks.

Our paper builds and extends on a literature on the labor market effects of ICT. To date, research has largely focused on the consequences of investments in computers and R&D.[7] We complement this research by providing novel evidence on the skill bias of broadband internet, a relatively recent technological change. Our findings are consistent with the widespread view that ICT is complementary with human capital. Technological changes that reduce quality-adjusted ICT prices – such as the arrival of broadband internet – should therefore increase skill demand and returns to skill. Our study also shows an important link between computerization and broadband adoption in firms. When broadband internet becomes available, it is not randomly adopted; instead, it is more quickly adopted in firms in which complementary factors are abundent, including computers and skilled workers. These findings conform to the predictions of a model of endogenous technology adoption where firms' choices reflect principles of comparative advantage (see e.g. Beaudry and Green, 2003, 2005; Beaudry, Doms, and Lewis, 2010)

Our paper is also related to a literature on firm productivity and ICT. Estimating how adoption of new technology, such as broadband internet, affects productivity has proven difficult for several reasons. It is often difficult to access data on technology adoption which can be linked with firm-level information on output and factor inputs.[8] Another key challenge is the likelihood that some determinants of production are unobserved to the econometrician but observed by the firm; if adoption of new technology depends on these determinants, then OLS estimates of production functions will be biased.[9] On top of

[7]See e.g. Krueger (1993), Berman, Bound, and Griliches (1994), DiNardo and Pischke (1997), Autor, Katz, and Krueger (1998), Machin and Van Reenen (1998), Beaudry and Green (2003; 2005), Acemoglu and Finkelstein (2008), Beaudry, Doms, and Lewis (2010), and Lewis (2011). Acemoglu (2003), Bond and Van Reenen (2007) and Goldin and Katz (2007) provide recent reviews of the extensive literature on technology-skill complementarity.

[8]For instance, typical annual accounts data reports labor costs as average (or total) wages for all workers, rather than wages by the skill level of the workers (Van Beveren, 2012). Moreover, statistical agencies have only recently started to systematically collect ICT information at the firm level (Draca, Sadun, and Van Reenen, 2007). In most cases, this information relates to broad measures of expenditure or usage of ICT, rather than precise measures of specific technological changes.

[9]Several studies illustrate the difficulty in drawing credible inferences absent an appropriate instrumental variable. For example, DiNardo and Pischke (1997) suggest that computer users possess unobserved skills which might have little to do with computers but which raise their productivity.

this, the use of inputs such as capital and labor could also be correlated with technology adoption and unobserved productivity, and therefore create bias in OLS estimates. These empirical challenges have meant that existing research has largely focused on demonstrating positive associations of ICT with productivity. Draca, Sadun, and Van Reenen (2007), in their Handbook of Information and Communication Technologies chapter, review the literature carefully and conclude that "none of the literature has produced convincing evidence of a causal impact of ICT on productivity, for example by analyzing a natural experiment".

In contrast to previous research, we have firm-level information on value added, capital, labor by skill level, and a precise measure of a specific technology adoption; as a source of exogenous variation in technology adoption, we exploit that the necessary infrastructure was established in different areas at different times; and following Levinsohn and Petrin (2003), we use intermediate inputs to proxy for unobserved productivity in the production function. This enables us to address the threats to identification and provide evidence on how broadband adoption in firms shifts the production technology and changes output for given inputs. By way of comparison, the estimated intention-to-treat effects allow us to examine the implications for workers and firms of the program that increased the availability of broadband internet, without invoking the full set of assumptions behind the structural estimation of the production function.

The paper unfolds as follows. Section 2 describes our data, before Section 3 discusses the expansion of broadband internet. Section 4 presents our identification strategy and empirical models. Section 5 describes our main findings, discusses their economic significance, and reports results from a number of robustness checks. Section 6 explores whether the task based framework can help interpret the skill complementarity of broadband internet. The final section offers some concluding remarks.

2 Data and descriptive statistics

Below we describe our data and sample selection, while details about the data sources and each of the variables are given in Appendix Table A1.

2.1 Data sources

Our analysis uses several data sources, which we can link through unique identifiers for each firm, employee, and municipality. The availability and reliability of Norwegian data are rated as exceptional in international quality assessments (see e.g. Atkinson, Rainwater, and Smeeding, 1995).

Firm and worker data. Our firm data come from administrative registers, which are updated annually by Statistics Norway and verified by the Norwegian Tax Authority. The data comprise all non-financial joint-stock firms over the period 2000-2008.[10] It contains detailed information from the firm's balance sheets on output (such as revenues) and inputs (such as capital, labor, intermediates) as well as 4-digit industry codes and geographical identifiers at the municipality level.

We merge the firm data set with a linked employer-employee registry that contains complete records of all firms and workers for the period 2000–2008. For every employee, we know his or her length of education, and annual labor income. In our baseline specification, we define an individual as skilled if he or she has a college or university degree, while individuals with less schooling are defined as unskilled. In parts of our analysis, we refine these often used proxies for skill levels: We divide unskilled individuals into medium skilled (high school graduates) and low skilled (no high school diploma).

Internet data. For the period 2001–2007, we have (i) data on broadband subscription for a stratified random sample of firms, and (ii) municipality-level information on availability of broadband internet to households (independently of whether they take it up). As explained in detail below, we will use the former to measure broadband adoption in firms, while the latter will be used to measure broadband availability rates, our instrumental variable. Throughout the paper, broadband internet is defined as internet connections with download speeds that exceed 256 kbit/s.[11]

Our data on broadband subscriptions of firms comes from the annual Community Survey on ICT Usage of Firms, performed by Statistics Norway. This survey includes information on the use of broadband internet in firms. In each year, the survey samples from the universe of joint-stock firms. The survey design is a stratified random sampling by industry and the number of employees.

The data on broadband availability comes from the Norwegian Ministry of Government Administration. The ministry monitors the supply of broadband internet to households, and the suppliers of broadband to end-users are therefore required to file annual reports about their availability rates to the Norwegian Telecommunications Authority. The availability rates are based on information on the area signal range of the local access points and detailed information on the place of residence of households. In each year and for every municipality, this allows us to measure the fraction of households for which broadband internet is available, independently of whether they take it up. In computing these availability rates at the municipality level, it is taken into account that multiple suppliers may offer broadband access to households living in the same area, so that double counting is avoided.

[10] These firms cover the vast majority of revenues and workers in the private sector. In 2001, for example, they cover 81 % of revenues and 71 % of workers.

[11] Before the expansion of broadband internet, all firms with a telephone connection would have dial-up access to internet, but limited to a bitrate of less than 56 kbit/s. Broadband internet facilitated internet use without excessive waiting times.

Socio-economic data. Most of our socio-economic data come from administrative registers provided by Statistics Norway. Specifically, we use a rich longitudinal database which covers every resident from 2000 to 2008. It contains individual demographic information (regarding gender, age, marital status and number of children), socio-economic data (educational attainment, income, employment status), and geographic identifiers for municipality of residence. The information on educational attainment is based on annual reports from Norwegian educational establishments, whereas the income data and employment data are collected from tax records and other administrative registers. The household information is from the Central Population Register.

Hourly wages and occupation. While the employer-employee registry contains data on employment status and annual wages of all workers, it does not provide information on hourly wages (or hours of work). When looking at the impact of broadband internet on hourly wages, we use data from Statistics Norway's Wage Statistics Survey for the years 2000-2008. In each year, the survey provides information on hourly wages and occupations. For employees in the private sector, the data is based on an annual stratified random sampling of all firms. The survey covers all employees in the public sector. Taken together, the information on hourly wages covers about 80 percent of Norwegian employees in every year (100 percent of the public sector employees and 70 percent of the private sector employees).

2.2 Sample selection and descriptive statistics

Table 1 displays summary statistics for the labor outcomes over time. The table shows averages of the employment rate and the (log) hourly wage over time, with standard deviations in parentheses. When estimating the employment effects, we consider the full population of individuals between the ages of 18 and 67 (the mandatory retirement age). To estimate the impact on hourly wages, we consider all workers between the ages of 18 and 67 who are recorded in the wage statistics surveys. Due to a sluggish Norwegian economy, the employment rates decline somewhat between 2000 and 2004. By comparison, hourly wages were steadily increasing over over the entire period 2001–2007.

Table 1. Summary statistics of labor outcomes

	2001	2004	2007	Overall
Employment rate	(level)	(level)	(level)	(level)
Total	0.72	0.70	0.72	0.71
	(0.45)	(0.46)	(0.45)	(0.45)
Unskilled	0.67	0.64	0.66	0.65
	(0.47)	(0.48)	(0.47)	(0.48)
Skilled	0.85	0.83	0.85	0.84
	(0.35)	(0.37)	(0.36)	(0.37)
Number of individuals, aged 18-67	2,829,739	2,899,342	2,991,389	20,327,515
Hourly wage (USD)	(log)	(log)	(log)	(log)
Total	2.95	3.05	3.12	3.04
	(0.27)	(0.28)	(0.30)	(0.30)
Unskilled	2.86	2.94	3.01	2.93
	(0.23)	(0.24)	(0.25)	(0.26)
Skilled	3.10	3.20	3.27	3.18
	(0.27)	(0.28)	(0.29)	(0.30)
Number of workers in wage survey, aged 18-67	1,161,912	1,246,036	1,349,481	8,759,388

Note: The employment rates are based on the population of workers between the ages of 18-67. The hourly wages are based on workers recorded in the wage survey between the ages of 18 and 67. (Un)Skilled comprises workers with(out) a college degree. Detailed descriptions of the variables are given in Appendix Table A1.

In the production function estimation, we use our data on joint-stock firms. In the interest of external validity, we exclude firms that are carrying out extraction of natural resources (including oil, gas and fish).[12] We refine this sample to be appropriate for estimation of production functions by focusing on firms with at least one employee in each of the two levels of skill. When looking at the intention-to-treat effects of the increased availability of broadband internet, we use the population of joint-stock firms (149,676 firms). By comparison, the analysis of broadband adoption in firms and the structural production function estimation are based on the sample of joint stock firms recorded in the internet survey (16,744 firms), for which we observe broadband adoption. We use sampling weights to produce representative estimates for the corresponding population of joint-stock firms.

Table 2 displays summary statistics for key firm variables over time.[13] The first panel displays the mean of output and non-labor inputs over time, with standard deviations in parentheses. In the production function, we use value added as the dependent variable, defined as revenues (total sales) net of intermediates (procurement of materials and intermediate inputs). We measure capital as the value of total stock of fixed assets. It is

[12]The production function estimates barely move if we include firms carrying out extraction of natural resources.

[13]Throughout this paper, all monetary figures are fixed at 1998 level after adjusting for inflation. For the figures expressed in U.S. dollars (USD), we have used the following exchange rate: NOK/USD = 7.5.

Table 2. Summery statistics of firm variables

	2001	2004	2007	Overall
Input-output (USD, thousands)	(log)	(log)	(log)	(log)
Revenues	7.63	7.63	7.74	7.65
	(1.05)	(1.06)	(1.16)	(1.09)
Value added	6.83	6.86	6.97	6.88
	(0.91)	(0.91)	(1.04)	(0.95)
Intermediates	6.61	6.59	6.68	6.61
	(1.79)	(1.80)	(1.84)	(1.81)
Capital	4.68	4.45	4.48	4.49
	(1.65)	(1.74)	(1.82)	(1.74)
Wage bills (USD, thousands)	(log)	(log)	(log)	(log)
Total	5.90	5.98	6.19	6.01
	(0.84)	(0.87)	(0.93)	(0.88)
Unskilled	5.52	5.60	5.80	5.63
	(0.99)	(1.01)	(1.08)	(1.02)
Skilled	4.08	4.17	4.36	4.19
	(1.44)	(1.50)	(1.60)	(1.51)
Number of firms				
Population	19,598	21,441	23,282	149,676
Survey	2,118	2,270	3,093	16,744

Note: This table shows summary statistics for the population of joint-stock firms, consisting of all joint-stock firms with at least one unskilled and one skilled employee. (Un)Skilled comprises workers with(out) a college degree. Detailed descriptions of the variables are given in Appendix Table A1.

evident that these variables are fairly stable over time, perhaps with a weakly increasing trend in revenues, value added and intermediates.

The second panel of Table 2 show means and standard deviations of wage bills by skill levels. There is a steady increase in the wage bills over time, especially for the high skilled. Following Fox and Smeets (2011), our analysis measures labor inputs by wage bills instead of the number of workers.[14] This has the advantage of making the measure of physical capital and human capital more comparable: Physical capital is measured in terms of monetary units to reflect the quality of the machinery employed, while using the wage bill to proxy for labor input also implies measuring labor in terms of its expense in order to better reflect its quality.

Appendix Figure A1 displays the distribution of firms by industry. This figure shows the industry composition in our survey sample and in the corresponding population of firms. The two main industries are manufacturing and wholesale/retail. This holds true both in terms of number of firms, aggregate value added, number of employees, and total wage bills. We can also see that the distributions in our sample (with sampling weights) closely mirror the distributions for the population of firms. The ability of our sampling weights to produce representative estimates are confirmed in Appendix Figures A2 and

[14]Our findings of skill-biased technical change from broadband adoption in firms are robust to measuring labor inputs by the number of workers instead of the wage bill.

A3: The former displays the distributions of output and inputs across firms, while the latter shows the time trends in these variables.

Appendix Table A2 reports estimates from a standard Cobb-Douglas production function, based on the survey sample (with sampling weights) and the population of firms. The first two columns report OLS estimates, while the last two columns use the method for estimating production functions proposed by Levinsohn and Petrin (2003). It is evident that whether we use the survey sample or the population of firms matters little for the estimated output elasticities. We can also see that our estimates align well with the findings in previous studies. As predicted by theory, OLS overstates the labor coefficients because the level of inputs chosen is positively correlated with unobserved productivity. The magnitudes of the output elasticities of capital and labor are comparable to what found in previous studies using micro data (see e.g. Pavcnik, 2002; Fox and Smeets, 2011).

3 Expansion of broadband internet

Over the past decade, many OECD countries were planning the expansion of services related to information and communications technology. In Norway, the key policy change came with the National Broadband Policy, introduced by the Norwegian Parliament in the late 1990s. This section provides details about the program and describes the expansion of broadband internet.[15]

The program. The National Broadband Policy had two main goals. The first was to ensure supply of broadband internet to every area of the country at a uniform price. The second was to ensure that the public sector quickly adopted broadband internet.

The Norwegian government took several steps to reach these goals. First and foremost, it invested heavily in the necessary infrastructure. The investment in infrastructure was largely channeled through the (state-owned) telecom company Telenor, which was the sole supplier of broadband access to end-users in the early 2000s and continues to be the main supplier today. Moreover, virtually all broadband infrastructure was, and still is, owned and operated by Telenor.

Second, local governments were required to ensure supply of broadband internet by 2005 to local public institutions, such as administrations, schools, and hospitals (St.meld.nr. 49, 2002–2003). To assist municipalities in rural areas, the federal government provided financial support through a funding program known as *Høykom*. Local governments could receive funds from this program by submitting a project plan that had to be reviewed by a program board with expert evaluations. The stated aim was to ensure broadband availability throughout the country. Once approved, financial support was provided in the

[15] Our discussion draws on Bhuller, Havnes, Leuven, and Mogstad (2013).

initial years of broadband access, thus making it possible for public institutions to cover relatively high initial costs.[16]

Supply and demand factors. The transmission of broadband signals through fiber-optic cables required installation of local access points. Since 2000, such access points were progressively rolled out, generating considerable spatial and temporal variation in broadband availability. The staged expansion of access points was in part due to limited public funding, but also because Norway is a large and sparsely populated country. There are often long driving distances between the populated areas, which are mostly far apart or partitioned by mountains or the fjord-gashed shoreline.[17]

The documents describing the National Broadband Policy and the roll-out of broadband access points (see St.meld.nr. 38 (1997-1998); St.meld.nr. 49 (2002-2003); Bhuller, Havnes, Leuven, and Mogstad, 2013), suggest the main *supply factors* determining the timing of roll-out are topographical features and existing infrastructure (such as roads, tunnels, and railway routes), that slow down or speed up physical broadband expansion.[18] Based on the program accounts, we expect the potential *demand factors* to be related to public service provision, income level, educational attainment, and the degree of urbanization in the municipality.

Evolution of broadband availability and usage. Appendix Figure A4 shows the variation in our measure of broadband availability to households across municipalities and over time. By 2000, broadband transmission centrals were installed in the cities of Oslo, Stavanger, and Trondheim, as well as in a few neighboring municipalities of Oslo and Trondheim. However, because of limited area signal range, broadband internet was available for less than one-third of the households in each of these municipalities. More generally, the figure illustrates that for a large number of municipalities there was no broadband availability in the first few years, whereas most municipalities had achieved fairly high availability rates in 2005. Moreover, there is considerable variation in availability rates within the municipalities in these years. Indeed, few municipalities experience a complete shift from no availability to full availability in a given year; rather, access points were progressively

[16]During the period 1999–2005, the Høykom program received more than 1000 such applications and co-funded nearly 400 projects, allocating a total of NOK 400 million. From 2002, the Ministry of Education and Research co-financed another scheme *(Høykom skole),* providing financial support for broadband infrastructure in public schools. There are virtually no private schools in Norway.

[17]The Norwegian territory covers about 149,400 square miles, an area about the size of California or Germany, with around 13 % and 6 % of those regions' populations (in 2008), respectively. The country is dominated by mountainous or high terrain, as well as a rugged coastline stretching about 1,650 miles, broken by numerous fjords and thousands of islands.

[18]The reason is that the transmission of broadband signals through fiber-optic cables required installation of local access points. In areas with challenging topography and landscapes, it was more difficult and expensive to install the local access points and the fiber-optic cables. Furthermore, the existing infrastructure mattered for the marginal costs of installing cables to extend the availability of broadband within a municipality and to neighboring areas.

rolled out within and across municipalitites, generating a continuous measure of availability rates that display considerable temporal and spatial variation (even conditional on year and municipality fixed effects).

Appendix Figure A5 summarizes the evolution of broadband availability to households and broadband usage in firms between 2001 and 2007. In each year, we report the overall means and the distributions across municipalities. There is considerable variation in both availability and usage, across municipalities and over time. The pattern in Figure A5 suggests a strong association between broadband availability to households and broadband usage in firms. This indicates that our measure of broadband availability is a fairly good proxy for the supply of broadband to firms, which we do not have direct information on.[19] Section 5 provides a more detailed regression-based analysis of the link between our measure of broadband availability rates and broadband adoption in firms.

4 Identification strategy

Randomizing broadband adoption is not feasible: We cannot in practice force firms to adopt a new technology. One can, however, think of a field experiment which randomizes broadband availability at the municipality level. The randomization would break the correlation between availability rates and unobserved determinants of productivity and labor outcomes. The intention of our identification strategy approach is to mimic this hypothetical experiment. Our source of exogenous variation comes from the staged installation of broadband infrastructure, generating spatial and temporal variation in broadband availability and adoption.

4.1 Regression model of intention-to-treat effects

To estimate the intention-to-treat effects of the increased availability of broadband internet, we specify the following panel data regression:

$$y_{imt} = x'_{imt}\delta_0 + z_{mt}x'_{imt}\delta_1 + w'_{imt}\theta + \eta_m + \tau_t + u_{imt}, \tag{1}$$

where z_{mt} is the availability rate of broadband internet in municipality m in period t. Unobservable determinants of production that are fixed at the municipality level will be controlled for through the municipality indicators (η_m), just like common time shocks are absorbed by the year indicators (τ_t). Throughout the paper, all standard errors are clustered at the municipality level and robust to heteroskedasticity.[20]

[19]Strictly speaking, all we need for the IV estimation is a variable that exogenously shifts some firms' take up of broadband internet. For example, if the supply of broadband to households were a noisy proxy for the supply to firms, this could generate a weak first stage for our instrument (which we do not have) but it would not be a violation of exclusion or independence conditions.

[20]There are 428 municipalities. Our standard errors change little if we instead cluster at the regional

We use model (1) to estimate the intention-to-treat effects on the labor outcomes and the productivity of high and low skilled workers. In the labor outcome regressions, y_{imt} is the (log) hourly wage or employment status of individual i in municipality m and in year t, x is is a vector of mutually exclusive dummy variables for educational attainment, and w is a vector of controls for gender, potential experience (linear and squared terms), and a full set of (4-digit) industry indicators. In these regressions, the coefficients δ_0 capture the pre roll-out mean wage or employment rate of workers with different levels of education, while the coefficients of primary interest δ_1 measure the interaction effects between educational attainment and broadband availability.

In the production function estimation, y_{imt} is the (log) value-added of firm i in municipality m and in year t, x is is a vector of inputs (in log), and w includes a full set of (4-digit) industry indicators. The coefficients δ_0 are then capturing the pre roll-out output elasticities of capital, skilled labor, and unskilled labor, whereas the coefficients of primary interest δ_1 measure the interaction effects between these input factors and broadband availability. Because x includes a constant term, we allow broadband availability to directly affect output through a change in the intercept.

4.2 Assessing the identification strategy

The key threat to identification is that the timing of the broadband roll-out might be related to different underlying trends in labor outcomes or productivity across municipalities. Before turning to a more detailed regression-based analysis that addresses this concern, we provide a graphical depiction of the timing of the broadband roll-out and of how the output elasticities and the returns to skill change with increased availability of broadband.

Timing of the broadband roll-out. Our identification strategy– which controls for municipality and year fixed effects – is motivated by two features of the program that expanded broadband availability. First, most of the supply and demand factors tend to vary little over time. Second, the timing of the roll-out is unlikely to co-vary with key correlates of labor outcomes and productivity.

To investigate whether the data is consistent with these program features, we first regress z_{mt} on municipality and time fixed effects as well as time-varying supply and demand factors. We find that 88 % of the variation in broadband availability can be attributed to time-invariant municipality characteristics and common time effects, while less than 1 % of the variation in broadband availability can be attributed to a large set of time-varying variables.[21]

level (of which there is 46). See Appendix Tables B3 and B4.

[21] The time-varying variables include demographic factors (income level, education, share of population residing in a densely populated locality, size of population, and level of unemployment), inputs and output (municipality averages of revenues, intermediates, capital stock, number of workers and wage bill), industry structure (number of firms, employment share in manufacturing, employment share in wholesale,

Second, we examine the relationship between the timing of broadband roll-out and baseline municipality characteristics. To this end, we estimate the following equation

$$\Delta z_{mt} = \eta_m + [\theta_t \times w_m]' \, \psi_t + \epsilon_{mt} \tag{2}$$

where $\Delta z_{mt} = z_{mt} - z_{m,t-1}$, and θ_t is a vector of year fixed effects. We let w_m include municipality-level information from year 2000 on demography, average levels of inputs and output, industry structure, and skill composition. Demography includes income level, education, share of population residing in a densely populated locality (an urbanization indictor), size of population and level of unemployment. For inputs and output, we have included municipality averages of revenues, intermediates, capital stock, number of workers and wage bill. As measures of industry structure, we use number of firms, employment share in manufacturing, employment share in wholesale, employment share in construction, and employment share in services. We measure skill composition as the shares of wages and workers by skill level. On top of all this information from year 2000, w_m includes municipality-level averages of the growth rates in wages and employment over the pre roll-out period 1998-2000.

Appendix Figure A6 plots the estimated coefficients from the vector ψ_t for every t (and the associated 95 % confidence intervals). Our results show that the timing of the expansion does not correlate with baseline industry structure, the levels of output and inputs, the skill composition, or the growth rates in labor outcomes prior to the expansion of broadband. The only pattern we can find is that broadband expansion is correlated with urbanization until 2002. From 2003 and onwards, there appears to be no systematic relationship between the timing of the broadband expansion and this variable.

Taken together, the evidence presented in Appendix Figure A6 suggest the roll-out of broadband availability is unrelated to key observable correlates of labor outcomes and productivity. Nevertheless, a concern is that there are differential underlying trends in the outcomes of interest depending on urbanization or some unobserved characteristic. To examine whether our estimates are biased because of differential trends by urbanization, we perform two robustness checks. First, we make sure that our estimates are robust to excluding firms or workers in the capital (Oslo) or in the three big cities. Second, we explicitly allow for differential trends by urbanization. This is done by interacting urbanization with linear and quadratic time trends. The estimates barely move. In addition, we take steps to examine whether other sources of differential trends are biasing our estimates. To check that the estimated effects are not driven by time-varying observable factors, we report results with and without a large set of time-varying controls for the potential supply and demand factors (discussed in Section 3). We also show robustness to

employment share in construction, and employment share in services), and skill composition (shares of wages and workers by skill level).

allowing for differential time trends across municipalities by interacting baseline covariates with time trends and by including linear municipality specific trends.

Event-study illustration. An advantage of the continuous nature of our measure of broadband availability is that it helps in obtaining precise estimates while credibly controlling for potential confounders. At the same time, providing a graphical depiction of the identificication strategy is more complicated in our context with spatial and temporal variation in treatment intensity, as compared to the usual difference-in-differences setting with a binary treatment variable. We still give a graphical illustration of the basic idea of our identification strategy in the spirit of an event study.

To provide a graphical illustration, it is helpful to recenter the data such that both cause and effect occur at time zero: In each municipality, time zero represents the year with the strongest growth in broadband availability.[22] By doing so, we can visually examine how the output elasticities and the returns to skill change around 'the event' of the largest increase in broadband availability. Separately for each time period before and after this event, we regress log value added on log capital, log skilled labor, and log unskilled labor; and we regress log hourly wage on a dummy for being a skilled worker while controlling for gender and potential experience. The first (second) graph of Figure 1 shows that the event of the sharp rise in availability rates from time -1 to zero is associated with a substantial increase (decrease) in the estimated output elasticity of (un)skilled labor. The third graph of this figure shows how the estimated return to skill increases after this rise in availability rates.

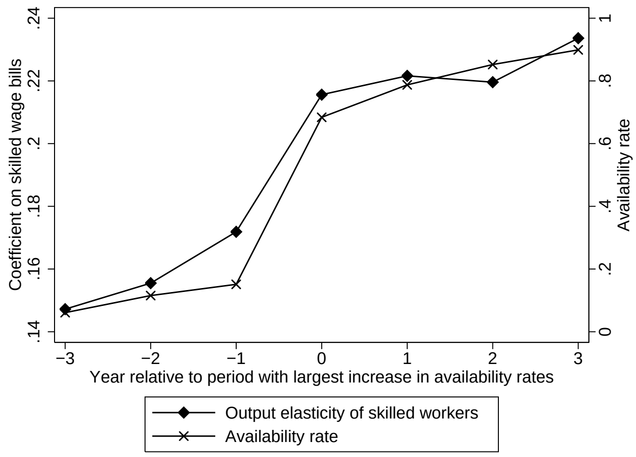
The time series evidence presented in Figure 1 is only suggestive of skill complimentarity of broadband internet, since it may be driven by, for example, other secular changes in the labor market or the macroeconomy more generally. In Appendix Figure B1, we control for year and municipality fixed effects in the period-specific estimation of the wage regressions and the production functions. It is interesting that the patterns of labor productivity and skill premium in Appendix Figure B1 are quite similar to the simple time series evidence in Figure 1.

Another challenge to interpreting the time series evidence in Figure 1 is that we have an unbalanced panel of municipalities before and after time zero, depending on which year time zero represents. As a result, composition effects as opposed to actual dynamics might drive the observed pattern. In Appendix Figure B2, we use a smaller window around time zero, which makes the panel data much more balanced. This figure compares the time series in output elasticities and skill premium with only 6 and 5 time periods. It is reassuring to find that the patterns do not materially change. As shown

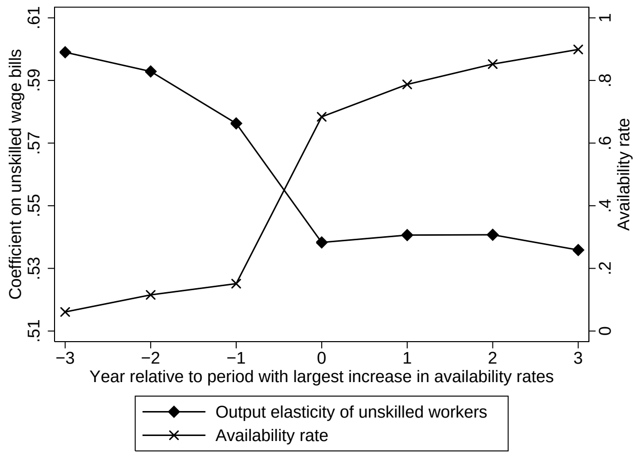
[22]For example, if a municipality experienced the largest increase in the availability rate from 2003 to 2004, then time zero represents 2004 for this municipality. By comparison, if another municipality had the largest increase in the availability rate from 2005 to 2006, then time zero represents 2006 for this municipality.

Figure 1. Output elasticites and skill premiums, pre and post the largest increase in availability rates (period 0)

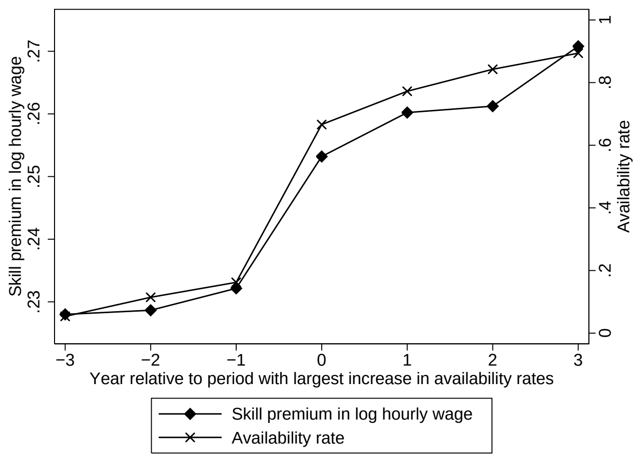
(a) Output elasticity: Skilled labor



(b) Output elasticity: Unskilled labor



(c) Return to Skill: Hourly wage



Note: Time zero represents the year with the strongest growth in availability rates in a given period. In each period, we estimate Cobb-Douglas production functions and wage regressions. Graphs (a) and (b) report period-specific OLS estimates of the output elasticity of skilled and unskilled labor. Graph (c) reports period-specific OLS estimates of log hourly wage on a dummy for skilled and controls for gender and potential experience.

in Appendix Figure B1, this conclusion holds true also if we combine a smaller window with controls for municipality and year fixed effects. By controlling for these variables, we mimick the baseline regression model by looking within municipalities while eliminating other secular changes over time in the labor market or the macroeconomy more generally. Regardless of whether or not we add these controls, the time patterns point to strong skill complementarity of broadband internet. In any case, compositional changes should not matter for the estimated coefficients in model (1), where we have a balanced sample of municipalities over the entire period.

4.3 Broadband adoption and technological change in production

Economic theory views the production technology as a function describing how a collection of factor inputs can be transformed into output, and it defines a technological change as a shift in the production function (i.e., a change in output for given inputs). To directly examine whether broadband adoption in firms causes a technological change in production, we will exploit that adoption increased as a result of the program that expanded broadband availability. This can be represented by the following system of equations, where the second stage represents a Cobb-Douglas production function with exponents that potentially change with the adoption of broadband internet:

$$y_{imt} = x'_{imt}\beta_0 + D_{imt}x'_{imt}\beta_1 + w'_{imt}\xi + \lambda_m + \tau_t + \varepsilon_{imt}, \tag{3}$$

while the first stages are given by

$$\begin{aligned} D_{imt} &= x'_{imt}\delta + z_{mt}x'_{imt}\phi + w'_{imt}\zeta + \gamma_m + \theta_t + \nu_{imt} \\ D_{imt}x_{1,imt} &= x'_{imt}\delta_1 + z_{mt}x'_{imt}\phi_1 + w'_{imt}\zeta_1 + \gamma_{1,m} + \theta_{1,t} + \nu_{1,imt} \\ \vdots &= \vdots \\ D_{imt}x_{n,imt} &= x'_{imt}\delta_n + z_{mt}x'_{imt}\phi_n + w'_{imt}\zeta_n + \gamma_{n,m} + \theta_{n,t} + \nu_{n,imt} \end{aligned} \tag{4}$$

where D_{imt} is a dummy variable which is equal to one if firm i in municipality m has broadband internet in year t (and zero otherwise), n denotes the number of input factors, and the remainder of the notation is the same as in equation (1).[23]

The availability rate z_{mt} serves as an instrument for broadband adoption in firms. While exogeneity of the instrument is sufficient for a causal interpretation of the intention-to-treat effects from equation (1), IV estimation of equations (3) and (4) require stronger assumptions. In particular, we have to assume that increased availability affects productivity and wages only through broadband adoption in firms, and not directly in any other way. We take several steps to challenge this exclusion restriction, finding suggestive evidence in

[23] In line with previous studies using micro data to estimate Cobb-Douglas production functions, we do not impose constant return to scale (see e.g. Pavcnik, 2002; Fox and Smeets, 2011).

favor of the assumption.

Another concern is that the factor inputs in x_{imt} could be correlated with broadband adoption and unobserved productivity. Following Levinsohn and Petrin (2003, hereafter LP), we take a more structural approach to address this threat to identification of the production function. LP uses a structural model of an optimizing firm to derive the conditions under which intermediate inputs can be used to proxy for unobserved productivity in the production function.[24] We refer to Appendix E for more details of the LP approach.

5 Empirical results

5.1 Intention-to-treat effects

We use model (1) to estimate the intention-to-treat effects on the labor outcomes and output elasticities of different types of workers. These estimates are informative about the effects on workers and firms of the program that increased the availability of broadband internet.

Worker evidence. Table 3 presents the effects of increased broadband availability on wages and employment. When estimating the employment effects, we consider the full population of individuals between the ages of 18 and 67. The impact on hourly wages pertain to workers aged 18-67 who are recorded in the wage statistics surveys. In columns 1 and 3, we follow much of the previous literature in defining an individual as skilled if he or she has a college degree, while individuals with less schooling are defined as unskilled. In columns 2 and 4, we report estimates from specifications where we divide unskilled into medium skilled (high school graduates) and low skilled (no high school diploma).

The results show that increased availability of broadband internet improves the labor outcomes of skilled individuals. For instance, the estimates imply that a 10 percentage point increase in broadband availability in a municipality raises wages of skilled workers in that local labor market by about 0.2 percent. By comparison, we find evidence of a decline in wages of low skilled individuals, but no significant change in their employment rate. To put the size of the labor market effects into perspective, we calculate counterfactual labor outcomes that would have occurred in the absence of the broadband expansion. A counterfactual outcome is measured as the actual outcome minus the predicted effect of broadband availability on the outcome. Consider the predicted effect on (log) wages of of (un)skilled labor. In each year, we compute this as the broadband availability rate z_{mt} multiplied by the coefficient on the interaction between broadband availability and

[24]Levinsohn and Petrin (2003) extend on Olley and Pakes (1996) by using intermediate inputs instead of investments as a proxy for unobserved productivity. This addresses the problem that investment is zero in a non-trivial number of cases.

Table 3. Intention-to-treat effects on labor outcomes

	Log hourly wage		Employment	
	2 skills	3 skills	2 skills	3 skills
	(1)	(2)	(3)	(4)
Unskilled	2.939***		0.691***	
	(0.00455)		(0.00262)	
Low skilled		2.905***		0.664***
		(0.00431)		(0.00231)
Medium skilled		2.977***		0.731***
		(0.00454)		(0.00288)
Skilled	3.169***	3.171***	0.734***	0.737***
	(0.00420)	(0.00407)	(0.00480)	(0.00477)
Availability×				
Unskilled	-0.00622		0.000794	
	(0.00455)		(0.00252)	
Low skilled		-0.0108***		-0.00392
		(0.00325)		(0.00244)
Medium skilled		-0.00793		0.00388
		(0.00600)		(0.00281)
Skilled	0.0178**	0.0202***	0.0208**	0.0225**
	(0.00720)	(0.00692)	(0.00920)	(0.00892)

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

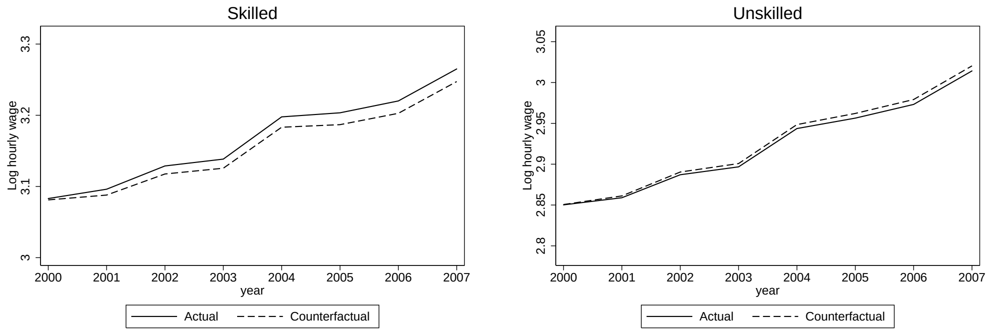
Note: Estimates are based on the model in equation (1). When estimating the employment effects, we consider the population of individuals between the ages of 18 and 67. The impact on hourly wages pertain to workers aged 18-67 who are recorded in the wage statistics surveys. (Un)Skilled comprises workers with(out) a college degree. Low skilled comprises individuals without high school diploma and medium skilled consists of high school graduates (without a college degree). The standard errors are clustered at the municipality level and robust to heteroskedasticity.

(un)skilled labor.

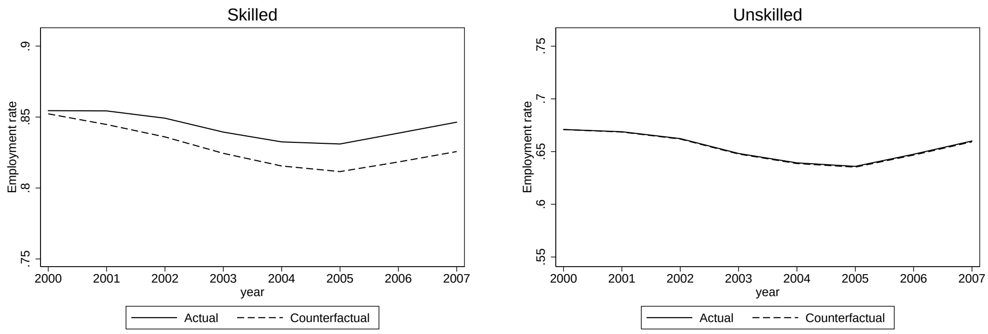
Figure 2 displays the actual time trends for wages and employment, as well as the predicted counterfactual time trends. Due to a sluggish Norwegian economy, the employment rates are declining between 2000 and 2004. The expansion of broadband internet mitigates the fall in employment rates among skilled workers. In 2005, for example, the employment rate for skilled workers was 1.9 percentage points higher than it otherwise would have been. By comparison, hourly wages increase throughout our sample period. In 2007, our estimates suggest the wages are (0.6 % lower) 1.8 % higher for (un)skilled workers than they would have been in the absence of the broadband expansion. Appendix Figure B3 complements by comparing the actual and counterfactual time trends in relative wage bills (i.e. the skilled wage bill divided by the unskilled wage bill). To compute the trends in relative wage bills, we combine the predicted effects on wages and employment. We find that the expansion of broadband internet contributes to an increase over time in the relative wage bill share of skilled workers.

Figure 2. Actual and counterfactual trends in labor outcomes

(a) Log hourly wages



(b) Employment rates



Note: Solid line = actual outome. Dashed line = counterfactual outcome in the absence of broadband internet expansion. A counterfactual outcome is measured as the actual outcome minus the predicted effect of broadband availability on the outcome. In each graph, the vertical axis covers four standard deviations of the labor outcome across municipalities and years.

Firm evidence. Table 4 presents the effects of increased broadband availability on output elasticities. We report estimates from specifications with two types of skill (college vs. no college) and three types of skill (college, high school graduates, no high school diploma). In line with the estimated changes in labor outcomes, the firm evidence suggest that increased availability of broadband internet is associated with a substantial increase (decrease) in the output elasticity of (low) skilled labor. By comparison, there is little if any change in the output elasticity of capital. A comparison of the changes in output elasticities and labor outcomes is informative about whether firms earn rent from the increased availability of broadband internet. To make this comparison we need to translate the output elasticiticy for, say, skilled labor into a measure of its marginal productivity, capturing that also the intercept and the other output elasticities change and thus affect firms' demand for skilled labor.[25] As shown in Appendix D, our estimates suggest that, in the short run, around 20 percent of the increase in marginal productivity of skilled workers is passed through to their wages. When we perform the same calculation for unskilled labor, we find an even smaller pass-through of changes in marginal productivity to wages.[26]

The relatively low pass-through of changes in marginal productivity to labor outcomes suggests that firms earn substantial rent from the expansion of broadband internet, at least in the short run. To quantify this, we use the estimates in column 1 of Table 4 to compute the predicted effect on output from increasing the availability of broadband internet. This prediction incorporates both the change in the intercept and the shifts in the output elasticities of capital, unskilled labor, and skilled labor. As such, it tells us the extent to which increased availability of broadband increases firm productivity, i.e. how much more output the firm produces for a fixed set of inputs. Although this prediction needs to be interpreted with caution, it suggests that a 10 percentage point increase in broadband availability raises output by 0.4 percent for given inputs.

Specification checks. In Appendix B, we present results from a battery of specification checks, all of which support our main findings. For brevity, we only report sensitivity checks for the specification with two types of skills, but we find that also the estimates based on three types of skills are robust to these checks.

In Appendix Tables B1 and B2, we challenge the validity of our identification strategy in several ways. Column 1 in these tables repeats the baseline estimates of the intention-

[25]A direct interpretation of the (change in the) intercept is difficult. The intercept represents the predicted value of the log value added when a firm uses one unit of each input factor; this value has no empirical counterpart because the actual range of these inputs does not include one.

[26]The relatively low pass-through to wages may be a short-run phenomenon or persist because of imperfect competition. The firms we consider are all in the private sector. Barth, Bratsberg, Hageland, and Raaum (2008) and Lunde and Grini (2007) suggest some scope for firms to adjust wages in response to changes in labor productivity, even in the short run. At the same time, there is considerabe churning in private sector firms in Norway (Hunnes, Moen, and Salvanes, 2009), suggesting that firms have some possiblity to adjust the skill mix of employment in the short run through how they replace workers or hire additional workers to expand.

Table 4. Intention-to-treat effects on output elasticities

	2 skills	3 skills
	(1)	(2)
Intercept	3.880***	4.537***
	(0.0965)	(0.0791)
Capital	0.100***	0.0981***
	(0.00495)	(0.00490)
Unskilled	0.576***	
	(0.0116)	
Low skilled		0.298***
		(0.00804)
Medium skilled		0.265***
		(0.00684)
Skilled	0.136***	0.134***
	(0.00678)	(0.00636)
Availability ×		
Intercept	-0.500***	-0.561***
	(0.111)	(0.0976)
Capital	-0.00169	0.000188
	(0.00750)	(0.00661)
Unskilled	-0.0226	
	(0.0234)	
Low skilled		-0.0274***
		(0.00934)
Medium skilled		0.0179*
		(0.00967)
Skilled	0.0755***	0.0645***
	(0.0166)	(0.0137)

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: This table uses the population of joint-stock firms. Estimates are based on the model in equation (1). (Un)Skilled comprises workers with(out) a college degree. Low skilled comprises individuals without high school diploma and medium skilled consists of high school graduates (without a college degree). The standard errors are clustered at the municipality level and robust to heteroskedasticity.

to-treat effects on labor outcomes and output elasticities, while columns 2 and 3 include a wide range of controls for time-varying demographic and industry characteristics. When we include these covariates, we find that the estimated intention-to-treat effects are quite similar to our baseline estimates. Columns 4-6 allow for different underlying trends in labor outcomes and output elasticities across municipalities. We first interact baseline (year 2000) covariates with a linear (column 4) and quadratic time trend (column 5). By including these controls, we allow the expansion of broadband internet to be related to different underlying time trends in labor outcomes and productivity across municipalities, depending on their initial characteristics (such as urbanization). A limitation of these robustness checks is that baseline characteristics may not adequately capture differential time trends across municipalities. Column 6 includes linear municipality-specific time trends. It is reassuring to find that the intention-to-treat effects do not change significantly when allowing for differential time trends across municipalities.

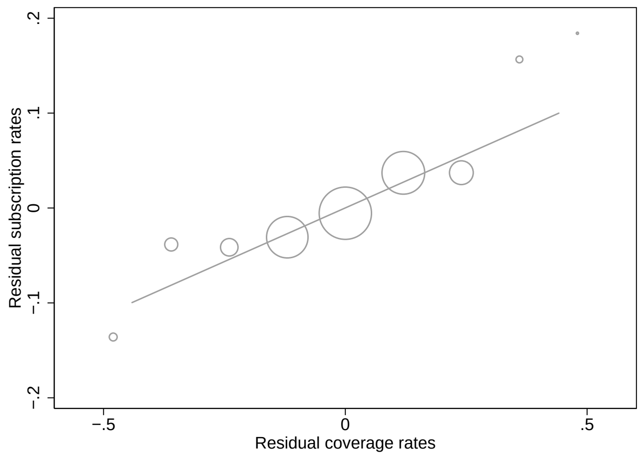
In the baseline specification, we measure local labor markets at the municipality level (of which there are 428). In Norway, this is the standard classification in official statistics (see Bhuller, 2009), and it ensures comparability with previous empirical work that relies on geographical segmentation of the Norwegian labor market (see e.g. Black, Devereux, and Salvanes, 2005). While we think the municipality level is a reasonable approximation of local labor markets, we take two steps to directly check for spillover or interaction effects. First, we exclude firms or workers in the capital (Oslo) or in the three big cities (which are the areas with most commuting) from the estimation of the intention-to-treat effects. We still find positive (negative) effects on the labor outcomes and output elasticitiy of (low) skilled workers. Second, we measure local labor markets at the regional level (of which there are 46). This conservative classification minimizes commuting across the local labor markets (see Bhuller, 2009). In this specification check, we measure the instrument (household availability rate) at the regional level, and re-estimate how broadband internet affects wages and productivity. Appendix Tables B3 and B4 display the estimates. It is reassuring to find that the results do not materially change.

Lastly, we make sure that the estimated output elasticities are robust using the LP approach to control for correlation between input levels and the unobserved productivity. Appendix Table B5 displays the results from the LP approach. As an alternative to this approach, we also estimate intention-to-treat effects on output elasticities where inputs are kept fixed at their values in 2001. Appendix Table B5 shows that the conclusion of skill complementarity of broadband internet do not change if we only use pre roll-out measures of input factors.

5.2 Broadband adoption in firms

The intention-to-treat results show how the increased availability of broadband internet affect labor outcomes and productivity of different types of workers. To interpret these

Figure 3. Association between broadband availability and usage rates, after taking out municipality, industry and year fixed effects



Note: This figure uses the survey sample of joint-stock firms. Bins are based on the residual subscription rates of firms with bin size = 0.12. The size of the circle represents the number of firms in each bin. Sampling weights are used to ensure representative results for the population of joint-stock firms. The Y-axis reports residuals from a regression of broadband subscription rates of firms on municipality, industry and year fixed effects. The X-axis reports residuals from a regression of broadband availability rates of households on municipality, industry and year fixed effects.

results, an important first step is to understand the pattern of broadband adoption in firms.

Figure 3 draws a scatter plot of the broadband availability against the broadband user rates of firms, after taking out municipality, year and industry fixed effects. We let the size of the circle represent the number of firms in each bin. The figure shows a strong association between the availability and user rates. This suggests a strong impact on broadband adoption of the increase in broadband availability from the previous year. To quantify this relationship, we use the survey sample of firms (for which we observe broadband adoption) to estimate the model:

$$D_{imt} = \delta z_{mt} + w'_{imt}\theta + \gamma_m + \sigma_t + \nu_{imt}. \tag{5}$$

We estimate the coefficient on the availability rate δ to be about 0.23 with a standard error of 0.04. This estimate implies that a 10 percentage point increase in broadband availability induces (an additional) 2.3 % of the firms to adopt broadband internet.

To understand what type of firms that quickly adopt broadband when it becomes available (compliers), we estimate equation (5) separately for different types of firms: We partition the baseline sample into six mutually exclusive groups by industry and share of workers with college degree (above and below median within each industry). Column 1 of Table 5 displays the proportion of the sample in each industry–skill group. The estimates of δ for the different types of firms are shown in the second column of Table 5. The proportion of the compliers of a given type is then calculated as the ratio of $\hat{\delta}$

for that subgroup to the $\hat{\delta}$ in the overall sample, multiplied by the proportion of the sample in the industry–skill group. Column 3 shows the distribution of the compliers by industry and skill intensity. We see that firms with a large share of high skilled workers are overrepresented among the compliers in every industry as compared to the sample of firms at large.

Columns 4–6 of Table 5 report the characteristics of each industry–skill group. Column 4 shows that in every industry the complier firms tend to be relatively large or productive (as measured by value added), while columns 5 and 6 show that they are more likely to deploy high skilled labor and use computers intensively. These findings suggest that when broadband internet becomes available, it is not randomly adopted; instead, it is more quickly adopted in firms in which complementary factors are abundent, including computers and skilled workers. This conforms to the predictions of a model of endogenous technology adoption where firms' choices reflect principles of comparative advantage (see e.g. Beaudry and Green, 2003, 2005; Beaudry, Doms, and Lewis, 2010).

Our findings complement previous research by Acemoglu and Finkelstein (2008) and Lewis (2011). The study by Acemoglu and Finkelstein (2008) looks at how changes in relative factor prices faced by U.S. hospitals affect their demand for capital and labor and their technology adoption decisions. They find that technology adoption in the health care sector is sensitive to relative factor prices, and that the skill mix of workers respond quickly to changes in technology. Lewis (2011) considers positive shocks to low skill labor supply across U.S. labor markets (stemming from immigrant flows), and finds that firms react quickly by changing their investments in new technology.

5.3 Broadband adoption and technological change

The above results showed that increased availability of broadband internet is associated with i) changes in the output elasticities of different types of workers, and ii) a substantial increase of broadband adoption in firms. Interpreted through the lense of the model in equations (3)-(4), the results point to broadband adoption in firms changing the production technology in a way that improves (worsens) the productivity of skilled (unskilled) workers. However, drawing such an inference requires stronger assumptions than exogeneity of the increase in broadband availability. In particular, we have to assume that increased availability affects labor productivity only through broadband adoption in firms, and not directly in any other way. Before presenting estimates of equations (3)-(4), we therefore challenge this exclusion restriction and explore alternative explanations of the intention-to-treat effects that are unrelated to broadband adoption in firms.

Alternative explanations. One alternative explanation is that increased availability of broadband internet among households changes demand for goods in favor of skilled labor. To examine this, we estimate the intention-to-treat effects of the increased availability of

Table 5. Characterizing complier firms.

	Composition of sample (1)	$\hat{\delta}$ (2)	Composition of compliers (3)	Log value added (4)	Share of skilled workers (5)	Share of workers using PC (6)	Number of obs. (7)
Manufacturing							
Low	0.19	0.17	0.16	14.16	0.11	0.32	2,216
High	0.19	0.20	0.19	14.35	0.31	0.56	2,218
Wholesale							
Low	0.22	0.21	0.23	13.51	0.11	0.57	2,609
High	0.22	0.24	0.26	13.69	0.32	0.73	2,609
Services							
Low	0.09	0.15	0.07	13.51	0.26	0.65	1,079
High	0.19	0.18	0.08	13.87	0.70	0.96	1,080
Overall	1.00	0.23	0.23	13.75	0.25	0.54	16,744

Note: We partition the survey sample of joint-stock firms into six mutually exclusive groups by industry and skill intensity (above and below median within each industry). Column 1 displays the proportion of the sample in each industry–skill intensity group. Column 2 reports estimates of δ from equation (4) for each group. The proportion of the compliers of a given type is then calculated as the ratio of $\hat{\delta}$ for that subgroup to the $\hat{\delta}$ in the overall sample, multiplied by the proportion of the sample in the industry–skill group. Column 3 shows the distribution of the compliers by industry and skill intensity. Columns 4–6 report characteristics of each industry–skill group. Sampling weights are used to ensure representative results for the population of joint-stock firms.

broadband among firms in the tradeable sector where demand is given by the world market as Norway is a small open economy. Consistent with the baseline results, Appendix Tables B6 and B7 show that increased availability of broadband internet increases (decreases) the output elasticities and wages of (un)skilled labor also in the tradeable sector. Another piece of evidence against this explanation is provided in Panel A of Appendix Table B8. Here, we estimate equation (5) with a dummy variable for receiving orders online as the dependent variable. There is no evidence of a significant effect of broadband availability on the probability of receiving orders online. Taken together, these results suggest that changes in demand for goods is not the key explanation of the intention-to-treat effects.

A second possible explanation of the intention-to-treat effects is that they are driven by changes in labor productivity and wages in firms that may have been directly affected by the expansion of broadband access. However, both the output elasticities and the labor outcome results barely move if we exclude telecom firms (including Telenor) or IT consultancy companies from the estimation sample (see Appendix Tables B9 and B10). It could also be that broadband adoption coincides with general technical upgrading in firms. For example, the estimated changes in labor productivity might be due to investments in computers at the time broadband is adopted. We investigate this by estimating equation (5) with the share of workers using PC as the dependent variable. The estimate reported in Panel B of Appendix Table B8 does not support this channel.

Another possible explanation is that broadband allows skilled workers to work from home, which then raises their output and pay potentially due to additional unmeasured hours of labor input. Indeed, it is conceivable that this effect could be present for high but not low skill workers if, for example, low skill workers do physical tasks that require on-site presence, whereas high skill workers can perform their jobs remotely. In this scenario, we would expect to see increases in productivity of skilled workers, and little if any change for low skilled workers. However, we find that broadband internet has a significant *negative* effect on the output elasticiticy of low skilled workers.

Exclusion restriction and production function estimates. The absence of evidence in favor of alternative explanations gives some confidence in the exclusion restriction that increased availability affects productivity and wages only through broadband adoption in firms, and not directly in any other way. Additional support is given by the placebo test presented in Appendix C. This placebo test exploits that under the exclusion restriction, there should be no intention-to-treat effect for firms that were not induced to adopt broadband because of the increase in availability.

Invoking the exclusion restriction, we estimate how broadband adoption in firms changes the production technology. Table 6 reports estimates based on OLS of equation (3) and IV of equations (3) and (4). The full set of first stage results are reported in Appendix Table B11. The first stages are strong, with large F-statistics on the excluded

Table 6. Broadband adoption and technological change.

	2 skills		3 skills	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Intercept	3.913***	3.854***	4.846***	4.801***
	(0.148)	(0.451)	(0.139)	(0.405)
Capital	0.0987***	0.0894***	0.110***	0.0980***
	(0.00736)	(0.0227)	(0.00764)	(0.0213)
Unskilled	0.583***	0.658***		
	(0.0179)	(0.0427)		
Low skilled			0.307***	0.352***
			(0.0197)	(0.0332)
Medium skilled			0.228***	0.247***
			(0.0116)	(0.0287)
Skilled	0.131***	0.0676**	0.129***	0.0844***
	(0.0105)	(0.0293)	(0.0120)	(0.0298)
Availability ×				
Intercept	-0.618***	-0.765	-0.835***	-0.961**
	(0.181)	(0.550)	(0.173)	(0.468)
Capital	0.00774	0.0212	-0.00572	0.0125
	(0.0111)	(0.0312)	(0.0109)	(0.0310)
Unskilled	-0.0297	-0.133**		
	(0.0215)	(0.0604)		
Low skilled			-0.0340*	-0.100*
			(0.0185)	(0.0512)
Medium skilled			0.0396***	0.0174
			(0.0135)	(0.0450)
Skilled	0.0910***	0.195***	0.0851***	0.160***
	(0.0111)	(0.0435)	(0.00756)	(0.0439)

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: This table uses the survey sample of joint-stock firms. OLS estimates are based on equation (3), whereas IV estimates are based on equations (3) and (4). Sampling weights are used to ensure representative results for the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. Low skilled comprises individuals without high school diploma and medium skilled consists of high school graduates (without a college degree). The standard errors are clustered at the municipality level and robust to heteroskedasticity.

instruments which mean weak instrument bias is not a concern. Both the OLS and IV estimates suggest that broadband adoption in firms is a skill biased technological change, shifting how factor inputs are transformed to output.[27] In particular, the output elasticity of skilled labor increases substantially, while broadband internet seems to be a substitute for unskilled labor. By comparison, there is little if any change in the output elasticity of capital. As shown in Appendix Table B12, these conclusions are robust to using the LP approach to control for correlations between factor inputs, broadband adoption and unobserved productivity.

Unfortunately, our data does not allow us to explore exactly how firms reorganize work and production in response to adopting broadband. There are, however, a few case studies that provides some insights.[28] The general argument made in these studies is that broadband internet complements workers in executing problem-solving, complex communication, and information-intensive tasks. A related study by Bartel, Ichniowski, and Shaw (2007) provide unique evidence on the channels through which a wide range of information technology affect firms and workers in one narrowly defined industry. Their study emphasizes that the adoption of IT-enhanced technology involves more than just installation of new equipment on the factory floor. Adoption of new information technologies make firms shift their business strategies and begin producing more customized products as well as improve the efficiency of all stages of the production process. Importantly, they show adoption of IT-enhanced technology increases the demand for technical and problem solvings and requires new human resource practices. Their empirical analysis suggest that adoption of new information technology quickly reduces production time, improves efficiency, and increases the demand for nonroutine problem solving skills.

6 Task based interpretation

To better understand the skill complementarity of broadband internet, we pursue a task based approach to skill biased technological change. Starting with Autor, Levy, and Murnane (2003), a growing literature suggest that ICT substitutes for workers in performing routine tasks – more amenable to automatization – and complements workers in executing nonroutine abstract tasks. To take the task based approach to our data, we use the wage statistics surveys with information on occupation codes at the 4-digit level.[29]

[27] Table 5 illustrates that the IV estimates are identified off a selective subgroup of early adopters of broadband internet; as a result, we need to be cautious in extrapolating these local estimates to the longer-run impact of broadband adoption for the population of firms at large. For the same reason, we also need to be cautious in comparing the OLS estimates to the IV estimates. The OLS estimates differ either because of endogeneity bias or because of heterogeneity across firms in the impact of adopting broadband internet.

[28] See e.g. the study of broadband adoption in the Canadian township of South Dundes (SNG, 2003).

[29] We observe occupation codes for about 52% of the workers in the wage statistics surveys. As a result, Tables 7 and 8 are based on a subsample of the data used in the estimation of the intention-to-treat effects on wages. However, when re-estimating the intention-to-treat effects on this subsample, we get similar

Table 7. Occupation types, wages and task intensities by skill category.

	Occupation types		Mean relative wage			Relative task intensities		
	Professional & Managerial	Other	All	Professional & Managerial	Other	$\hat{M}/\hat{A}$	$\hat{R}/\hat{A}$	Number of obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
A. 2 skill categories								
Unskilled	0.14	0.86	-0.09	0.20	-0.14	0.13	0.21	3,176,647
Skilled	0.66	0.34	0.21	0.30	0.02	-0.30	-0.47	1,409,686
B. 3 skill categories								
Low skilled	0.12	0.88	-0.13	0.16	-0.17	0.15	0.24	1,730,625
Medium skilled	0.17	0.83	-0.05	0.22	-0.10	0.11	0.18	1,446,022
Skilled	0.66	0.34	0.21	0.30	0.02	-0.30	-0.47	1,409,686

Note: We consider workers aged 18-67 who are recorded in the wage statistics surveys and for which we observe occupation code at the 4-digit level. The occupation codes are linked with measures of task intensity from the Dictionary of Occupational Title, as reported by Autor and Dorn (2013). In Panel A, (Un)Skilled comprises workers with(out) a college degree. In Panel B, Low skilled comprises individuals without high school diploma and medium skilled consists of high school graduates (without a college degree). Columns (1) and (2) show the occupation distribution by skill category. Following Autor and Dorn (2013), we define professional and managerial occupations as white-collar managerial, professional specialists, technical, finance, and public safety occupations. Columns (3)-(5) provide mean relative wage by type of occupation and skill category. The mean relative wage is defined as the average log hourly wage within each skill-occupation group relative to the overall sample mean. Columns (6) and (7) report relative task intensities by skill level. Following Autor and Dorn (2009, 2013), we calculate $\hat{M}/\hat{A}$ ($\hat{R}/\hat{A}$) as the mean of the logarithm of the ratio of the manual (routine) task content in an occupation to the abstract task content in the same occupation. Both measures are standardized with mean zero and variance one.

Table 8. Wage regressions with interactions between tasks and broadband availability

		Skill categories	
		2 skill levels	3 skill levels
Dep. variable: Log hourly wage	(1)	(2)	(3)
Abstract	0.371***	0.283***	0.272***
	(0.0142)	(0.0139)	(0.0140)
Routine	-0.0641***	-0.0664***	-0.0699***
	(0.00653)	(0.00573)	(0.00576)
Manual	0.0248***	0.0156**	0.0138*
	(0.00791)	(0.00769)	(0.00740)
Availability×Abstract	0.173***	0.157***	0.157***
	(0.0320)	(0.0298)	(0.0297)
Availability×Routine	-0.0357***	-0.0344***	-0.0338***
	(0.00798)	(0.00766)	(0.00791)
Availability×Manual	0.00200	0.00145	0.00273
	(0.0115)	(0.0107)	(0.0104)
Additional controls:			
Skill categories		√	√
Availability*Skill category		√	√

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: We consider workers aged 18-67 who are recorded in the wage statistics surveys and for which we observe occupation code at the 4-digit leve. The occupation codes are linked with measures of task intensity from the Dictionary of Occupational Title (DOT), as reported by Autor and Dorn (2013). Following Autor, Levy, and Murnane (2003), we convert the DOT measures into percentiles of the task distribution. (Un)Skilled comprises workers with(out) a college degree. Low skilled comprises individuals without high school diploma and medium skilled consists of high school graduates (without a college degree). Column 1 presents results from a regression of log hourly wages on task intensities and their interaction with broadband availability in the local labor market. Column 2 adds indicator variables for two levels of skill and their interaction with broadband availability. Column 3 includes indicator variables for three levels of skills and their interaction with broadband availability. All regressions include fixed effects for year, municipality and industry, and controls for gender, years of experience and years of experience squared. Standard errors are heteroskedasticity robust and clustered at the municipality level.

We link these occupation codes with job task requirements from the DOT data base provided by Autor and Dorn (2013). The measured job task intensities are (nonroutine) abstract tasks, routine tasks and (nonroutine) manual tasks. Appendix Table B13 provides examples of workplace activities with different task intensities.[30]

A necessary condition for a task based explanation of the skill complementarity of broadband internet is that workers of different educational background actually cluster disproportionaly in occupations that require different tasks. Table 7 shows the occupational types, wages and task intensities for each skill category.[31] We find that college graduates tend to work in professional and managerial occupations that are pervasive at abstract tasks and pay more. By comparison, low educated workers are over-represented in poorly paid occupations that involve relatively little abstract tasks, but require more routine or manual tasks.

Motivated by these differences, we estimate wage regressions which include interactions between broadband internet and the tasks performed in jobs rather than (or in addition to) the educational credentials of workers performing those jobs. All regressions control for time, municipality, and industry fixed effects as well as (potential) experience and gender. The estimates are provided in Table 8. Column 1 shows the expansion of broadband internet re-enforced the wage premiums to workers performing abstract tasks. By comparison, the wages paid to jobs requiring routine tasks declined because of the broadband expansion. The estimates imply that, holding everything else equal, a 10 percentage point increase in broadband availability in a municipality raises (lowers) hourly wages of workers with abstract (routine) task intensity at the 75th percentile by 0.9 (0.2) percent, as compared to workers at the 25th percentile of the task intensity. Importantly, columns 2 and 3 show the estimates are quite similar when we control for skill levels and their interaction with broadband availability.

Taken together, the results presented in Tables 7 and 8 suggest an important mechanism behind the skill bias of broadband internet is that it complements non-routine abstract tasks but substitutes for routine tasks whilst not affecting manual tasks.

7 Conclusion

In 2009, the U.S. Congress asked for a plan that would provide affordable broadband service to all America's citizens. In other OECD countries, there has been similar calls for public funding to roll out broadband infrastructure. While government agencies are projecting broadband penetration rates to be important for productivity and wage growth,

results.

[30]See Autor, Levy, and Murnane (2003) and Autor and Dorn (2009) for detailed descriptions of how the task intensities are measured and intepreted.

[31]Following Autor and Dorn (2013), we define professional and managerial occupations as white-collar managerial, professional specialists, technical, finance, and public safety occupations.

there is little scientific evidence to substantiate these claims.

Using rich Norwegian data, we contribute by examining how broadband internet affects the labor outcomes and productivity of different types of workers. A public program with limited funding rolled out broadband access points, and provides plausibly exogenous variation in the availability and adoption of broadband internet in firms. Our results suggest that broadband internet improves (worsens) the labor outcomes and productivity of skilled (unskilled) workers. We explore several possible explanations for the skill bias of broadband internet. We find suggestive evidence that broadband adoption in firms complements skilled workers in executing nonroutine abstract tasks, and substitutes for unskilled workers in performing routine tasks.

Taken together, our findings have important implications for the debate about the role of government policies in the expansion of broadband infrastructure. Our estimates suggest that policy increasing the broadband penetration rates can be important in enhancing firm productivity. A related issue is why policy changes, even if they encourage productivity, do not always happen. One explanation is that established interests earning rents in the unreformed environment could be able to stave off reform. Examining who wins, who loses, and by how much could inform about the nature of these barriers and how to design compensation schemes. Our study points to the skill bias of broadband induced shift in production technology as a possible barrier to government investment in broadband infrastructure.

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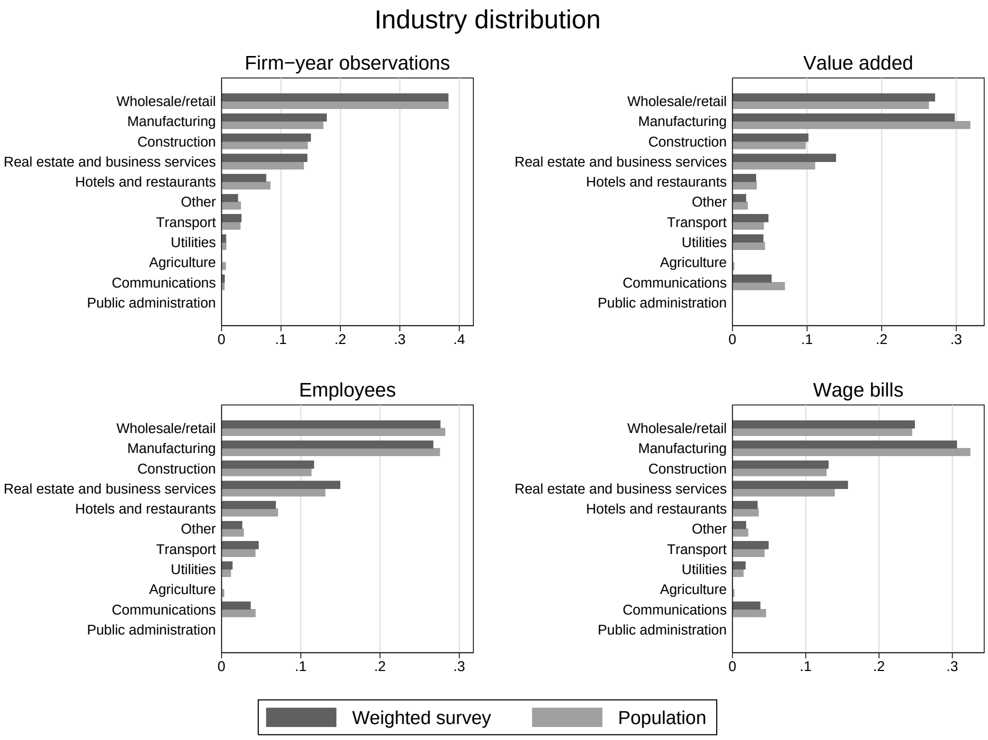
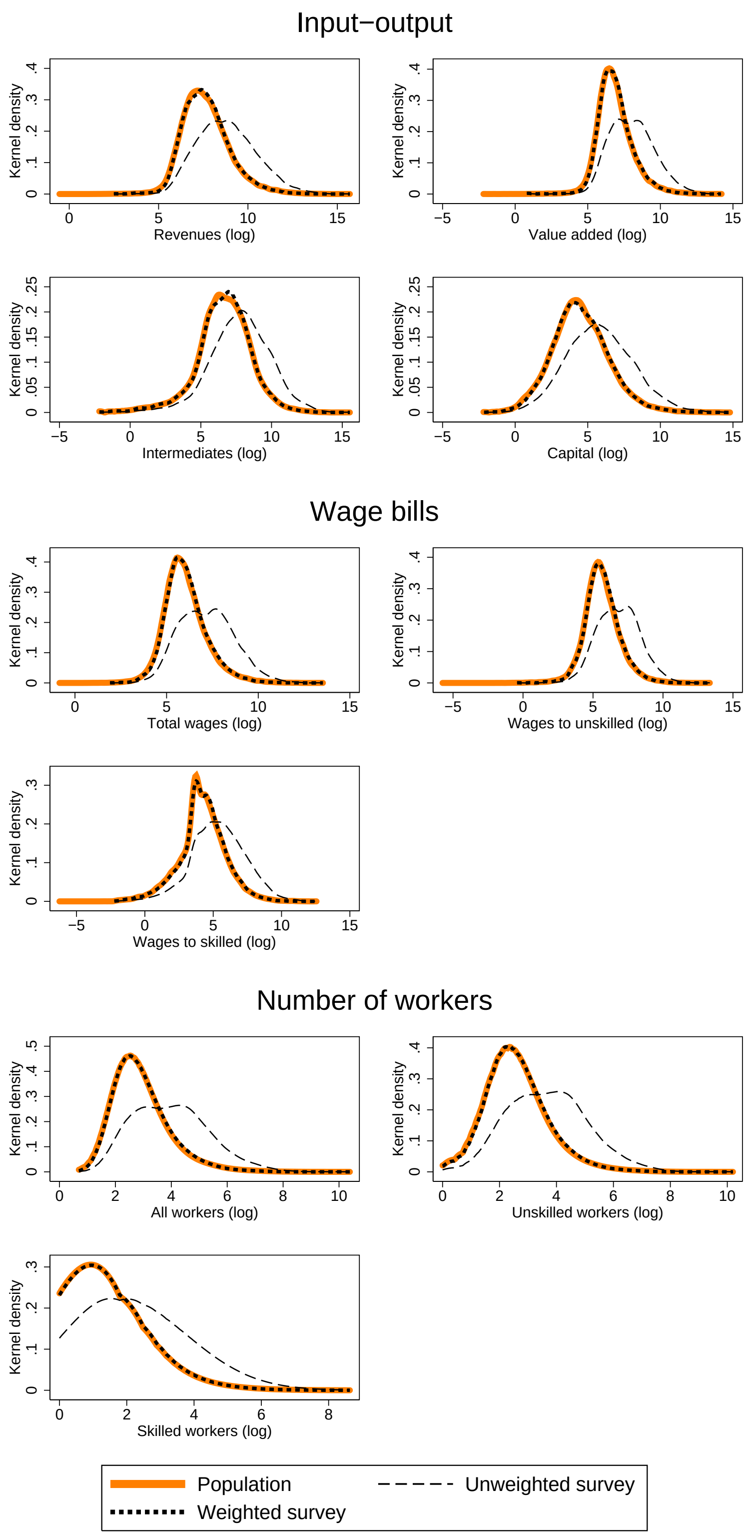
Appendix A: Data and expansion

Figure A1. Distribution of firms by industry



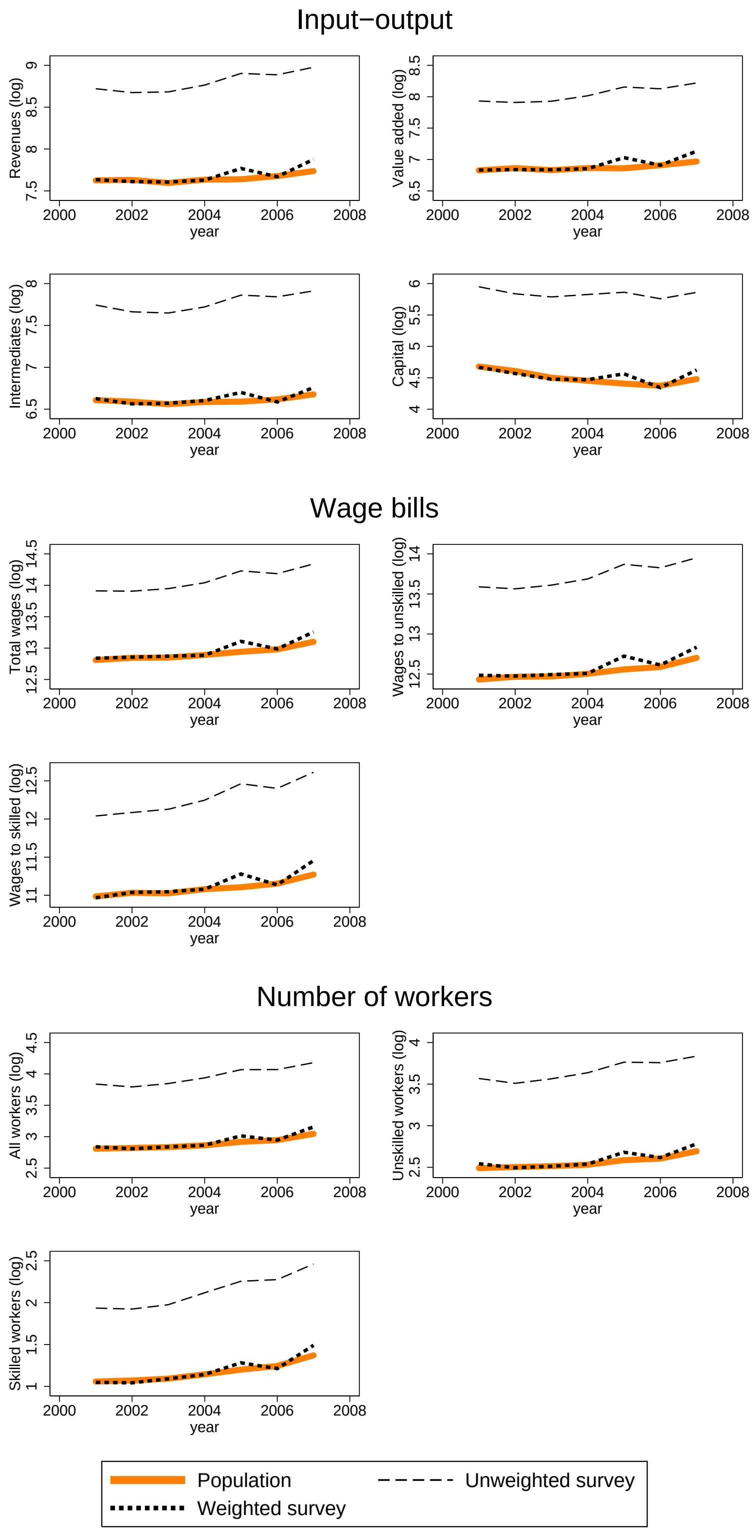
Note: The figure compares the weighted survey sample of joint-stock firms to the population of joint-stock firms. Sampling weights are used to ensure representative results for the population of joint-stock firms.

Figure A2. Cross-sectional distribution of key firm variables



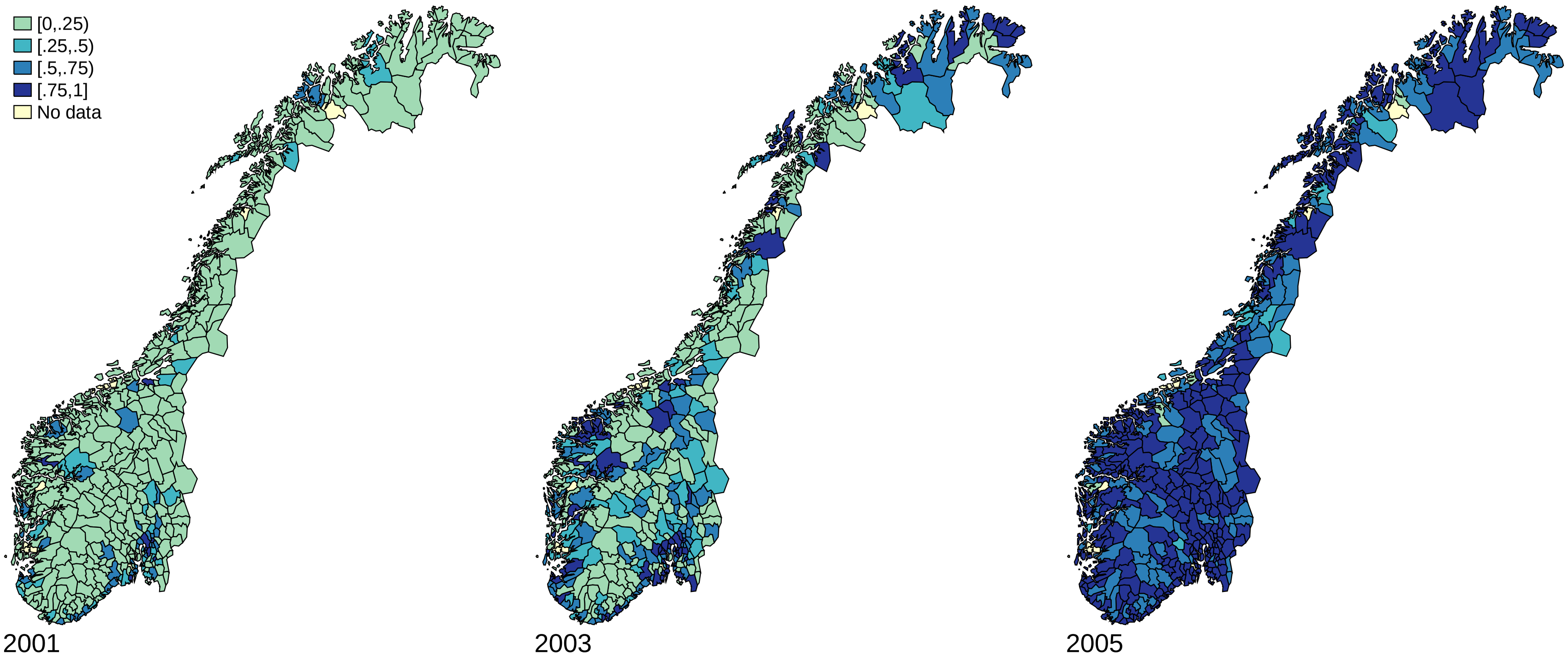
Note: The figures compare the weighted survey sample of joint-stock firms to the population of joint-stock firms. Sampling weights are used to ensure representative results for the population of joint-stock firms. Detailed descriptions of the variables are given in Appendix Table A1.

Figure A3. Time trends in key firm variables



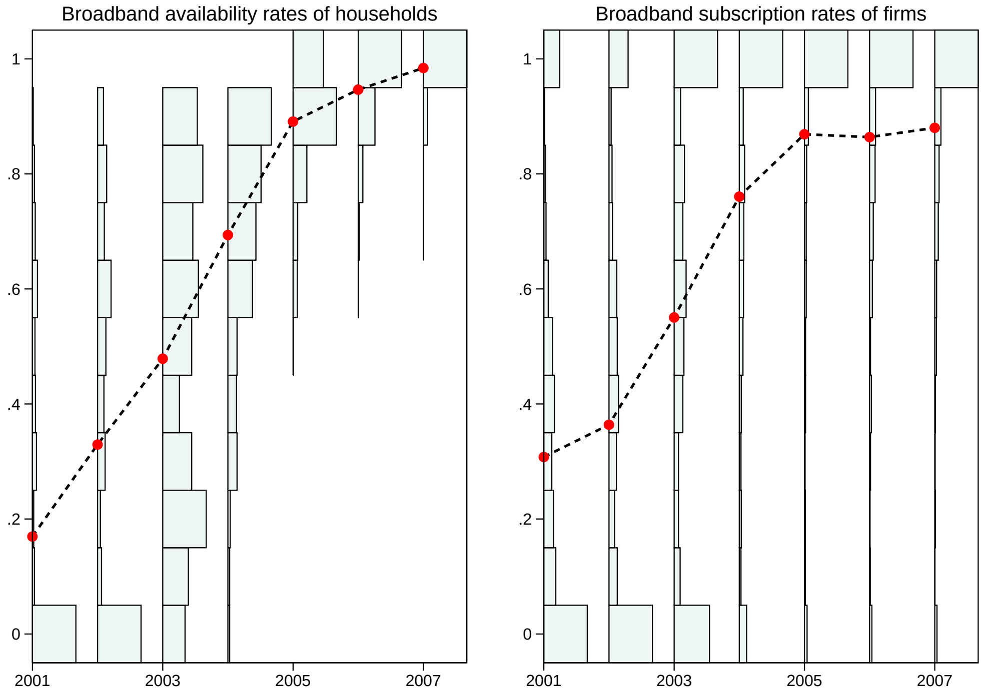
Note: The figures compare the weighted survey sample of joint-stock firms to the population of joint-stock firms. Sampling weights are used to ensure representative results for the population of joint-stock firms. Detailed descriptions of the variables are given in Appendix Table A1.

Figure A4. Geographical distribution of broadband availability rates.



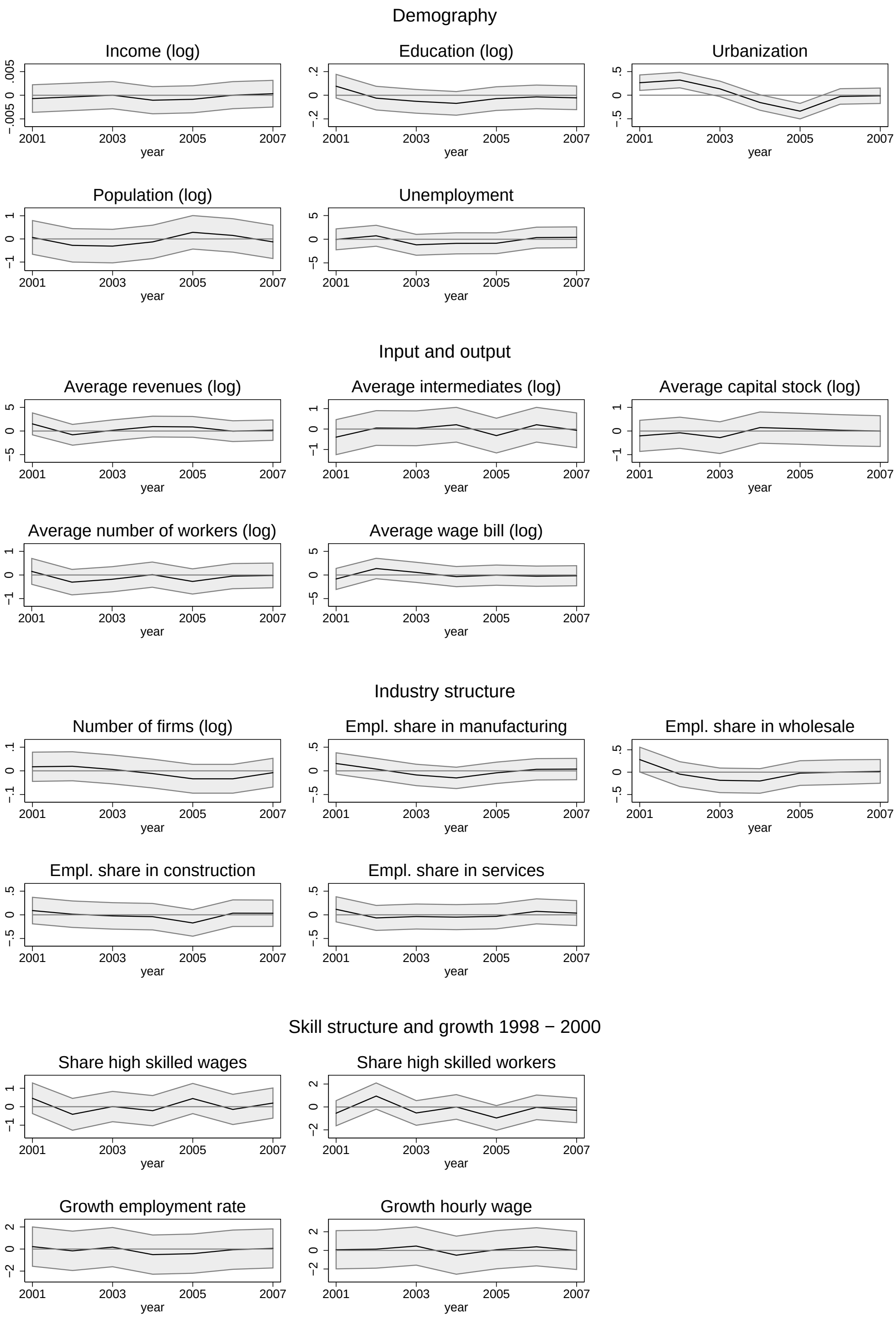
Note: The graphs show the geographical distribution of broadband availability rates of households in 2001, 2003 and 2005.

Figure A5. Broadband availability rates of households and broadband subscription rates of firms



Note: The graphs show the overall mean and distribution of broadband availability rates of households and broadband subscription rates of firms across municipalities for each year during the period 2001–2007.

Figure A6. Timing of broadband expansion and baseline covariates



Note: This figure report estimates from equation (2) of the vector ψ_t for every t (and the associated 95 % confidence intervals).

Table A1. Variable definitions

Variable	Description
Firm accounts	Source: The Account Statistics.
Revenues	Total sales by a firm in year t.
Intermediates	Procurement of materials and intermediate inputs of a firm in year t.
Capital	Value of total fixed assets of a firm in year t.
Value added	Sales minus intermediates of a firm in year t.
Industry	4-digit code classifying a firm's main activity in year t according to the Standard Industry Classification (SIC2002) system.
Municipality	4-digit code for the municipality in which a firm is located in year t.
Exports	Total value of exported goods of a firm in year t.
Imports	Total value of imported goods of a firm in year t.
Internet variables	Source: The community survey on ICT in firms
Broadband	Dummy variable for whether a firm has adopted broadband internet (speed at or above 256 kilobits per second) in year t.
Revenues from online orders	Dummy variable for whether at least part of a firm's total revenues comes from online orders in year t.
Employees	Source: Register of Employers and Employees and the Wage Statistics Survey.
Annual wages	Annual pre-tax wages in year t
Employment status	Dummy variable for whether annual wages exceed the substantial gainful activity threshold in year t (USD 6,850 in 2001), which defines employment in the Social Security System.
Hourly wages	Hourly pre-tax wage per October in year t.
Occupation	4-digit occupation code of a job in year t.
Individual characteristics	Source: National Education Database and Central Population Register.
Education level	Years of schooling.
Municipality	Municipality of residence in year t.
Age	The age of a worker in year t.
Potential experience	Age in year t - years of schooling - 7
Gender	The gender of a worker.

Variable	Description
Internet availability	Source: Norwegian Ministry of Government Administration.
Availability rate	Fraction of households in year t in a given municipality for which broadband internet is available, independently of whether they take it up.
Demographic controls	Source: Central Population Register.
Urbanization	Population share living in densely populated area in a given municipality in year t.
Income	Average annual disposable income across individuals aged 16–59 years in a given municipality in year t.
Education	Average years of schooling across individuals aged 16–59 in a given municipality in year t.
Unemployment	Unemployment rate among individuals aged 16–59 in a given municipality in year t.
Industry and firm controls	Source: The Account Statistics and Register of Employers and Employees.
Share of skilled workers	Share of employed workers with a college degree in a given municipality in year t.
Share of total wages to skilled workers	Share of the total wage bill paid to workers with a college degree in a given municipality in year t.
Share of employment by industry	Share of workers in the manufacturing/wholesale/service industry in a given municipality in year t.
Average input levels	Average level of capital stock/value added/number of workers/wages paid/revenues across firms in a given municipality in year t.
Growth in employment rate 1998-2000	Change from 1998 to 2000 in the average employment rate of workers aged 18-67 in a given municipality.
Growth in hourly wage 1998-2000	Proportional change from 1998 to 2000 in the average hourly wage of workers aged 18-67 in a given municipality.

Table A2. Production function estimates

	OLS		LP	
	Population	Weighted Survey	Population	Weighted Survey
Panel A: 1 skill category				
Intercept	1.971***	1.841***	4.172***	3.187***
	(0.0408)	(0.0851)	(0.0958)	(0.191)
Capital	0.0780***	0.0821***	0.104***	0.164***
	(0.00297)	(0.00497)	(0.019)	(0.019)
Labor	0.845***	0.856***	0.652***	0.676***
	(0.00351)	(0.00733)	(0.00480)	(0.00934)
Panel B: 2 skill categories				
Intercept	3.461***	3.380***	5.887***	4.695***
	(0.0455)	(0.0984)	(0.102)	(0.199)
Capital	0.0990***	0.106***	0.107***	0.194***
	(0.00399)	(0.00599)	(0.022)	(0.019)
Unskilled	0.558***	0.570***	0.410***	0.429***
	(0.0136)	(0.0141)	(0.0108)	(0.0143)
Skilled	0.198***	0.194***	0.138***	0.135***
	(0.0115)	(0.0127)	(0.00913)	(0.0105)
Observations	149,676	16,744	149,676	16,744

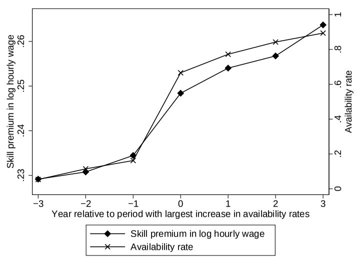
* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: The table compares estimates of Cobb-Douglas production functions based on the the weighted survey sample of joint-stock firms and the population of joint-stock firms. Sampling weights are used to ensure representative results for the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry.

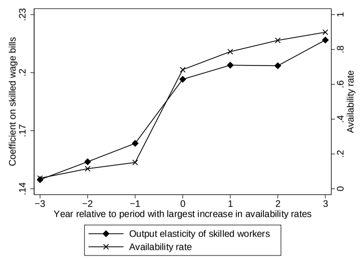
Appendix B: Specification checks and additional results

Figure B1. Output elasticites and skill premiums conditional on year and municipality fixed effects with varying window, pre and post the largest increase in availability rates (period 0)

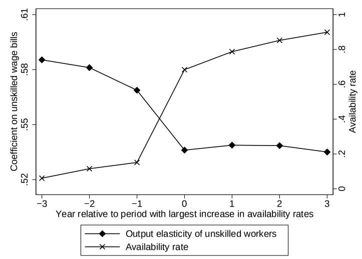
(a) Return to Skill: Hourly wage.



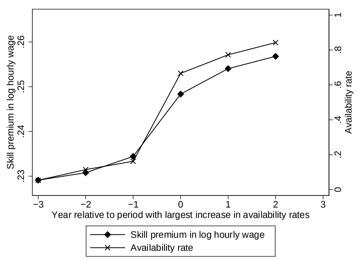
(b) Output elasticity: Skilled labor.



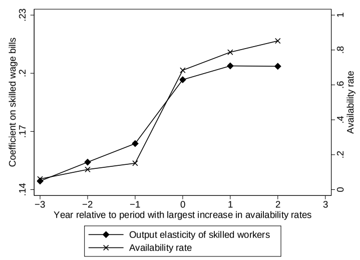
(c) Output elasticity: Unskilled labor.



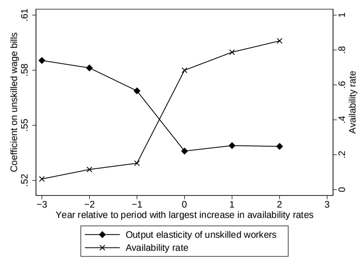
(d) Return to Skill: Hourly wage.



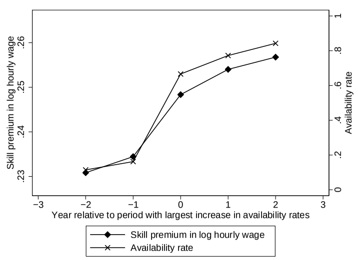
(e) Output elasticity: Skilled labor.



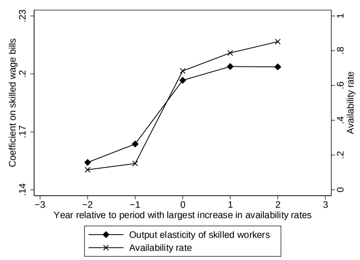
(f) Output elasticity: Unskilled labor.



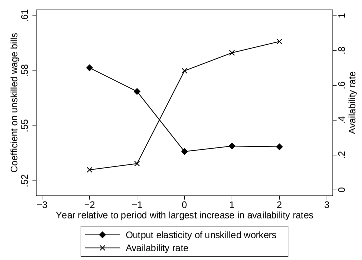
(g) Return to Skill: Hourly wage.



(h) Output elasticity: Skilled labor.



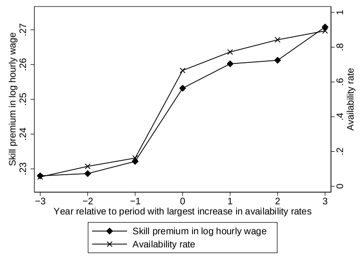
(i) Output elasticity: Unskilled labor.



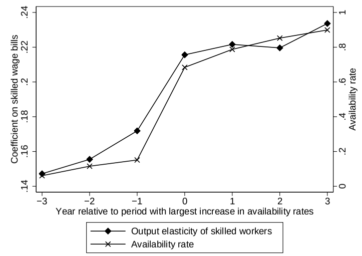
Note: Time zero represents the year with the strongest growth in availability rates in a given period. In each period, we estimate Cobb-Douglas production functions and wage regressions with year and municipality fixed effects. Graphs (b), (c), (e), (f), (h), and (i) report period-specific OLS estimates of the output elasticity of skilled and unskilled labor. Graphs (b), (d), and (g) report period-specific OLS estimates of log hourly wage on a dummy for skilled and controls for gender and potential experience.

Figure B2. Output elasticites and skill premiums with varying window, pre and post the largest increase in availability rates (period 0)

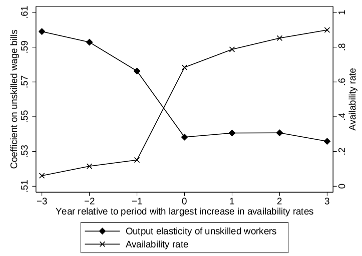
(a) Return to Skill: Hourly wage.



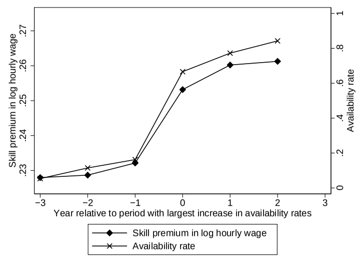
(b) Output elasticity: Skilled labor.



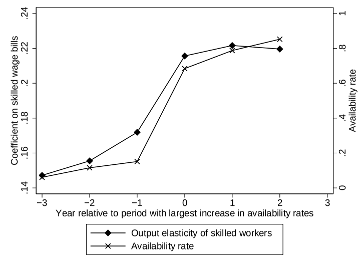
(c) Output elasticity: Unskilled labor.



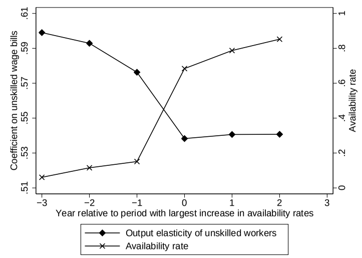
(d) Return to Skill: Hourly wage.



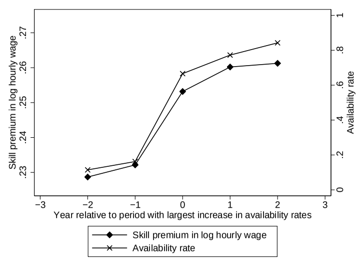
(e) Output elasticity: Skilled labor.



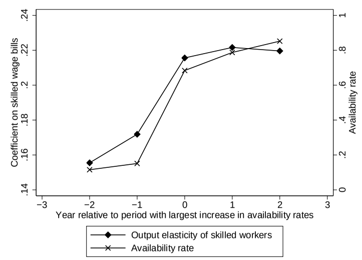
(f) Output elasticity: Unskilled labor.



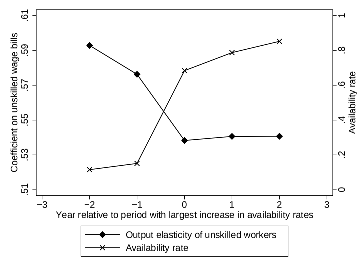
(g) Return to Skill: Hourly wage.



(h) Output elasticity: Skilled labor.

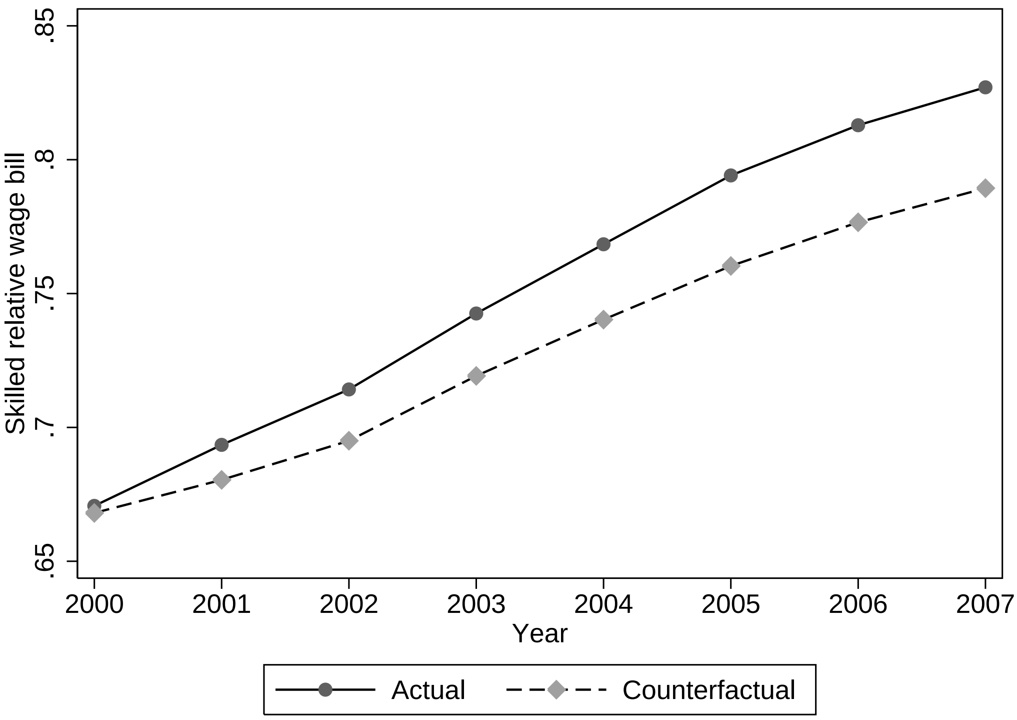


(i) Output elasticity: Unskilled labor.



Note: Time zero represents the year with the strongest growth in availability rates in a given period. In each period, we estimate Cobb-Douglas production functions and wage regressions. Graphs (b), (c), (e), (f), (h), and (i) report period-specific OLS estimates of the output elasticity of skilled and unskilled labor. Graphs (b), (d), and (g) report period-specific OLS estimates of log hourly wage on a dummy for skilled and controls for gender and potential experience.

Figure B3. Actual and counterfactual trends in relative wage bills.



Note: Solid line = actual outome. Dashed line = counterfactual outcome in the absence of broadband internet expansion. The counterfactual outcome is measured as the actual outcome minus the predicted effect of broadband availability on the relative wage bill of skilled workers using the intention-to-treat estimates for hourly wages and employment in Table 3.

Table B1. Specification checks for intention-to-treat effects on labor outcomes

		Baseline	Covariates		Time interacted with covariates		Linear muncipality trends
					Linear	Quadratic	
		(1)	(2)	(3)	(4)	(5)	(6)
Panel A:	Unskilled	0.691***	0.690***	0.691***	0.697***	0.697***	0.696***
Employment rate		(0.00262)	(0.00143)	(0.00129)	(0.000966)	(0.00104)	(0.000927)
	Skilled	0.734***	0.733***	0.733***	0.739***	0.739***	0.738***
		(0.00480)	(0.00379)	(0.00363)	(0.00233)	(0.00231)	(0.00238)
	Availability×						
	Unskilled	0.000794	0.00170	0.00140	-0.00637***	-0.00679***	-0.00522**
		(0.00252)	(0.00122)	(0.00125)	(0.00245)	(0.00257)	(0.00245)
	Skilled	0.0208**	0.0217***	0.0214***	0.0141**	0.0138**	0.0153**
		(0.00920)	(0.00797)	(0.00775)	(0.00595)	(0.00588)	(0.00596)
Panel B:	Unskilled	2.939***	2.939***	2.940***	2.943***	2.943***	2.945***
Log hourly wage		(0.00455)	(0.00391)	(0.00355)	(0.00174)	(0.00181)	(0.00197)
	Skilled	3.169***	3.170***	3.170***	3.174***	3.174***	3.175***
		(0.00420)	(0.00361)	(0.00327)	(0.00173)	(0.00185)	(0.00190)
	Availability×						
	Unskilled	-0.00622	-0.00714*	-0.00790**	-0.0119***	-0.0118***	-0.0140***
		(0.00455)	(0.00376)	(0.00336)	(0.00190)	(0.00199)	(0.00208)
	Skilled	0.0178**	0.0168***	0.0161***	0.0116***	0.0117***	0.00924**
		(0.00720)	(0.00639)	(0.00592)	(0.00335)	(0.00347)	(0.00366)
	Demographic		√	√	√	√	√
	Industry			√	√	√	√

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: All regressions include fixed effects for year, municipality and industry, and controls for gender, years of experience and years of experience squared. When estimating the employment effects, we consider the full population of individuals between the ages of 18 and 67. The impact on hourly wages pertain to workers aged 18-67 who are recorded in the wage statistics surveys. (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. Column 2 adds demographic controls to the baseline model, including municipality-level information on average household income, mean years of schooling, share of population residing in a densely populated locality, size of population and level of unemployment. Column 3 also includes industry controls, consisting of municipality averages of revenues, intermediates, capital stock, number of workers and wage bills as well as employment share in manufacturing, employment share in wholesale, employment share in services, and shares of wages and workers by skill level. Columns 4 and 5 interact linear and quadratic time trends with baseline values of these covariates. Column 6 includes municipality-specific linear time trends.

Table B2. Specification checks for intention-to-treat effects on output elasticities

	Baseline	Covariates		Time interacted with covariates: Linear	Time interacted with covariates: Quadratic	Linear municipality trends
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	3.880***	3.901***	3.876***	3.897***	3.896***	3.899***
	(0.0965)	(0.0964)	(0.0945)	(0.0961)	(0.0962)	(0.0967)
Capital	0.100***	0.101***	0.101***	0.101***	0.101***	0.101***
	(0.00495)	(0.00499)	(0.00486)	(0.00495)	(0.00496)	(0.00501)
Unskilled	0.576***	0.575***	0.577***	0.576***	0.576***	0.576***
	(0.0116)	(0.0116)	(0.0116)	(0.0117)	(0.0117)	(0.0119)
Skilled	0.136***	0.136***	0.135***	0.135***	0.135***	0.134***
	(0.00678)	(0.00680)	(0.00670)	(0.00675)	(0.00676)	(0.00689)
Availability ×						
Intercept	-0.500***	-0.525***	-0.498***	-0.524***	-0.522***	-0.527***
	(0.111)	(0.111)	(0.107)	(0.110)	(0.110)	(0.112)
Capital	-0.00169	-0.00232	-0.00249	-0.00282	-0.00287	-0.00284
	(0.00750)	(0.00752)	(0.00736)	(0.00749)	(0.00749)	(0.00757)
Unskilled	-0.0226	-0.0216	-0.0238	-0.0231	-0.0232	-0.0232
	(0.0234)	(0.0234)	(0.0232)	(0.0234)	(0.0235)	(0.0238)
Skilled	0.0755***	0.0761***	0.0766***	0.0774***	0.0776***	0.0781***
	(0.0166)	(0.0167)	(0.0166)	(0.0167)	(0.0167)	(0.0169)
Controls						
Demographic		√	√	√	√	√
Industry			√	√	√	√

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: This table uses the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry. Column (2) adds demographic controls to the baseline model, including municipality-level information on average household income, mean years of schooling, share of population residing in a densely populated locality, size of population and level of unemployment. Column 3 also includes industry controls, consisting of municipality averages of revenues, intermediates, capital stock, number of workers and wage bills as well as employment share in manufacturing, employment share in wholesale, employment share in services, and shares of wages and workers by skill level. Columns 4 and 5 interact linear and quadratic time trends with baseline values of these covariates. Column 6 includes municipality-specific linear time trends.

Table B3. Intention-to-treat effects on labor outcomes: Clustering and regional level

	Log hourly wage			Employment		
	Baseline	Cluster at region	Regional level	Baseline	Cluster at region	Regional level
	(1)	(2)	(3)	(4)	(5)	(6)
Unskilled	2.939***	2.939***	2.927***	0.691***	0.691***	0.686***
	(0.00455)	(0.00441)	(0.00882)	(0.00262)	(0.00268)	(0.00736)
Skilled	3.169***	3.169***	3.160***	0.734***	0.734***	0.730***
	(0.00420)	(0.00287)	(0.00622)	(0.00480)	(0.00534)	(0.00857)
Availability×						
Unskilled	-0.00622	-0.00622*	0.00912	0.000794	0.000794	0.00773
	(0.00455)	(0.00326)	(0.00891)	(0.00252)	(0.00278)	(0.00887)
Skilled	0.0178**	0.0178***	0.0298***	0.0208**	0.0208**	0.0255*
	(0.00720)	(0.00660)	(0.0111)	(0.00920)	(0.00881)	(0.0130)

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: When estimating the employment effects, we consider the full population of individuals between the ages of 18 and 67. The impact on hourly wages pertain to workers aged 18-67 who are recorded in the wage statistics surveys. (Un)Skilled comprises workers with(out) a college degree. The standard errors in columns 1 and 4 are clustered at the municipality level and in columns 2-3 and 5-6 at the regional level (see Bhuller, 2009). In columns 3 and 6 we measure availability rates as the average availability rate at the regional level. All regressions include fixed effects for year, municipality and industry and controls for gender, years of experience and years of experience squared.

Table B4. Intention-to-treat effects on output elasticities: Clustering, and regional level.

	Baseline	Cluster at region	Regional level
	(1)	(2)	(3)
Intercept	3.880***	3.880***	3.975***
	(0.0965)	(0.113)	(0.137)
Capital	0.100***	0.100***	0.117***
	(0.00495)	(0.00506)	(0.00836)
Unskilled	0.576***	0.576***	0.543***
	(0.0116)	(0.0129)	(0.0170)
Skilled	0.136***	0.136***	0.144***
	(0.00678)	(0.00668)	(0.0104)
Availability $\times$			
Intercept	-0.500***	-0.500***	-0.721***
	(0.111)	(0.0944)	(0.152)
Capital	-0.00169	-0.00169	-0.0139
	(0.00750)	(0.00681)	(0.00913)
Unskilled	-0.0226	-0.0226	-0.00135
	(0.0234)	(0.0237)	(0.0228)
Skilled	0.0755***	0.0755***	0.0890***
	(0.0166)	(0.0197)	(0.0230)

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: This table uses the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. The standard errors in columns 1 are clustered at the municipality level and in columns 2 and 3 at the regional level (see Bhuller (2009)). In column 3 we measure availability rates as the average availability rate the regional level. All regressions include fixed effects for year, municipality and industry.

Table B5. Intention-to-treat effects on output elasticities: LP approach and fixed inputs

	Full sample		Firms observed in 2001	
	Baseline	LP	Baseline	Fixed inputs
	(1)	(2)	(3)	(4)
Intercept	3.880***	5.935***	3.624***	3.730***
	(0.0965)	(0.164)	(0.105)	(0.123)
Capital	0.100***	0.107***	0.0995***	0.0992***
	(0.00495)	(0.028)	(0.00507)	(0.00560)
Unskilled	0.576***	0.460***	0.586***	0.589***
	(0.0116)	(0.0108)	(0.0119)	(0.0139)
Skilled	0.136***	0.104***	0.145***	0.148***
	(0.00678)	(0.00536)	(0.00650)	(0.00681)
Availability ×				
Intercept	-0.500***	-0.186*	-0.814***	0.00954
	(0.111)	(0.110)	(0.126)	(0.121)
Capital	-0.00169	-0.00854	-0.0126*	0.0124
	(0.00750)	(0.00563)	(0.00696)	(0.00901)
Unskilled	-0.0226	-0.0236	0.00818	-0.0548**
	(0.0234)	(0.0200)	(0.0247)	(0.0216)
Skilled	0.0755***	0.0561***	0.0831***	0.0501***
	(0.0166)	(0.0128)	(0.0167)	(0.0153)

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: This table uses the population of joint-stock firms but columns 3 and 4 restrict the sample to joint-stock firms which are observed in 2001. (Un)Skilled comprises workers with(out) a college degree. In column 2 we apply the Levinsohn Petrin method and in column 4 we use 2001 values of inputs in every year. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry.

Table B6. Intention-to-treat effects on output elasticities in tradable and non-tradable sectors.

		Above/below median			
	Baseline	Trade/Revenues		Geographic concentration	
		High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)
Intercept	3.880***	3.537***	4.470***	3.781***	3.973***
	(0.0965)	(0.122)	(0.137)	(0.160)	(0.110)
Capital	0.100***	0.108***	0.0944***	0.115***	0.0938***
	(0.00495)	(0.00678)	(0.00715)	(0.00676)	(0.00695)
Unskilled	0.576***	0.557***	0.569***	0.565***	0.579***
	(0.0116)	(0.0153)	(0.0148)	(0.0191)	(0.0124)
Skilled	0.136***	0.185***	0.0878***	0.148***	0.125***
	(0.00678)	(0.0108)	(0.00875)	(0.0102)	(0.00709)
Availability ×					
Intercept	-0.500***	-0.310**	-0.958***	-0.461***	-0.509***
	(0.111)	(0.142)	(0.157)	(0.168)	(0.129)
Capital	-0.00169	-0.0147*	0.00815	-0.00744	-0.00515
	(0.00750)	(0.00828)	(0.00971)	(0.00907)	(0.00815)
Unskilled	-0.0226	-0.0214	-0.00152	-0.0387	-0.00513
	(0.0234)	(0.0272)	(0.0223)	(0.0308)	(0.0190)
Skilled	0.0755***	0.0669***	0.0887***	0.0926***	0.0621***
	(0.0166)	(0.0193)	(0.0185)	(0.0214)	(0.0119)
Mean of tradability measure		0.28	0.02	0.00024	0.00007
N	149,676	74,619	75,057	68,379	81,297

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: This table uses the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry. We use two measures of tradability. In columns 2 and 3, we measure tradability in each 4-digit industry by dividing total levels of exports and imports by the value added of firms. In columns 4 and 5, we follow Jensen and Kletzer (2005) in measuring tradability by the geographic concentration of an industry, defined as the Herfindahl index of employment shares across municipalities in each 4-digit industry. For both measures, we estimate separately for firms in industries with values of tradability above and below the median in the baseline firm sample.

Table B7. Intention-to-treat effects on wages in tradable and non-tradable sectors.

		Above/below median			
	Baseline	Trade/Revenues		Geographic concentration	
		High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Log hourly wage					
Unskilled	2.939***	3.007***	2.976***	2.991***	2.959***
	(0.00455)	(0.00438)	(0.00291)	(0.00412)	(0.00214)
Skilled	3.169***	3.296***	3.149***	3.221***	3.162***
	(0.00420)	(0.00695)	(0.00868)	(0.00866)	(0.00732)
Availability ×					
Unskilled	-0.00622	0.000217	-0.00924***	0.00166	-0.00161
	(0.00455)	(0.00494)	(0.00312)	(0.00403)	(0.00250)
Skilled	0.0178**	0.0230**	0.0422***	0.0275**	0.0463***
	(0.00720)	(0.0103)	(0.0140)	(0.0133)	(0.0120)
Mean of tradability measure		0.45	0.04	0.41	0.08
N	8,759,388	989,470	1,522,999	2,284,875	1,576,368

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: We include workers aged 18-67 who are recorded in the wage statistics surveys. In columns 2-9 we restrict the sample to workers employed by one of the firms in our sample. (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry. We use two measures of tradability. In columns 2, 3, 6 and 7 we measure tradability in each 4-digit industry by dividing total levels of exports and imports by the value added of firms. In columns 4, 5, 8 and 9, we follow Jensen and Kletzer (2005) in measuring tradability by the geographic concentration of an industry, defined as the Herfindahl index of employment shares across municipalities in each 4-digit industry. For both measures, we estimate separately for workers in industries with values of tradability above and below the median in the baseline firm sample.

Table B8. Intention-to-treat effects on E-commerce and computerization.

	Estimate (2)	Dependent mean (3)
Panel A: E-commerce:		
Dep. variable: Receiving orders online	-0.00265	0.26
	(0.0319)	
Panel B: Technical upgrading		
Dep. variable: Share of workers using a PC	-0.00217	0.58
	(0.0228)	

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: This table uses the survey sample of joint-stock firms. Sampling weights are used to ensure representative results for the population of joint-stock firms.All regressions include fixed effects for year, municipality and industry. Standard errors are heteroskedasticity robust and clustered at the municipality level. The standard errors are clustered at the municipality level and robust to heteroskedasticity.

Table B9. Intention-to-treat effects on output elasticities excluding telecom firms and IT consultancy companies.

	Baseline	No telecom	No IT consultancy
Intercept	3.880***	3.876***	3.829***
	(0.0965)	(0.0957)	(0.0987)
Capital	0.100***	0.101***	0.0985***
	(0.00495)	(0.00499)	(0.00504)
Unskilled	0.576***	0.575***	0.586***
	(0.0116)	(0.0116)	(0.0119)
Skilled	0.136***	0.137***	0.130***
	(0.00678)	(0.00678)	(0.00698)
Availability ×			
Intercept	-0.500***	-0.476***	-0.483***
	(0.111)	(0.106)	(0.111)
Capital	-0.00169	-0.00380	-0.00208
	(0.00750)	(0.00747)	(0.00770)
Unskilled	-0.0226	-0.0215	-0.0224
	(0.0234)	(0.0233)	(0.0229)
Skilled	0.0755***	0.0743***	0.0747***
	(0.0166)	(0.0166)	(0.0160)
N	149,676	148,973	145,282

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: Column 1 uses the population of joint-stock firms. Column 2 excludes telecom firms (NACE code 64), whereas column 3 excludes IT consultancy firms (NACE code 72). (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry.

Table B10. Intention-to-treat effects on labor outcomes excluding telecom firms and IT consultancy companies.

		Baseline (1)	No telecom employees (2)	No computer workers (3)
Panel A:	Unskilled	0.691***	0.689***	0.690***
Employment rate		(0.00262)	(0.00266)	(0.00268)
	Skilled	0.734***	0.731***	0.732***
		(0.00480)	(0.00477)	(0.00486)
	Availability×			
	Unskilled	0.000794	0.00109	0.00117
		(0.00252)	(0.00255)	(0.00257)
	Skilled	0.0208**	0.0211**	0.0212**
		(0.00920)	(0.00924)	(0.00932)
Panel B:	Unskilled	2.939***	2.935***	2.936***
Log hourly wage		(0.00455)	(0.00443)	(0.00450)
	Skilled	3.169***	3.165***	3.166***
		(0.00420)	(0.00410)	(0.00423)
	Availability×			
	Unskilled	-0.00622	-0.00698	-0.00665
		(0.00455)	(0.00439)	(0.00444)
	Skilled	0.0178**	0.0180**	0.0187**
		(0.00720)	(0.00716)	(0.00737)
	Experience	√	√	√
	Female	√	√	√

* $p < 0.10$, ** < 0.05, *** $p < 0.01$.

Note: In column 1, when estimating the employment effects, we consider the full population of individuals between the ages of 18 and 67. The impact on hourly wages pertain to workers aged 18-67 who are recorded in the wage statistics surveys. Column 2 excludes workers in telecom firms (NACE code 64), whereas column 3 excludes workers in IT consultancy firms (NACE code 72). (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry and controls for gender, years of experience and years of experience squared.

Table B11. First stage regressions

Dependent variable:	Internet (1)	Internet × Capital (2)	Internet × Unskilled (3)	Internet × Skilled (4)
Intercept	-0.897***	-15.27***	-15.56***	-13.17***
	(0.190)	(2.162)	(2.259)	(2.101)
Capital	0.0142	0.354***	0.182	0.163
	(0.0100)	(0.123)	(0.123)	(0.105)
Unskilled	0.0428*	0.646***	0.860***	0.598**
	(0.0219)	(0.246)	(0.253)	(0.233)
Skilled	0.0665***	0.849***	0.863***	0.905***
	(0.0151)	(0.173)	(0.187)	(0.152)
Availability ×				
Intercept	0.919***	5.630**	5.034**	4.311*
	(0.215)	(2.431)	(2.535)	(2.342)
Capital	-0.00392	0.603***	-0.0512	-0.0402
	(0.0110)	(0.135)	(0.135)	(0.116)
Unskilled	-0.0197	-0.344	0.298	-0.283
	(0.0245)	(0.277)	(0.283)	(0.260)
Skilled	-0.0375**	-0.515***	-0.492**	0.189
	(0.0166)	(0.187)	(0.203)	(0.163)
F-value (instruments)	41.4	56.7	38.5	28.6

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: This table uses the survey sample of joint-stock firms. Sampling weights are used to ensure representative results for the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry and controls for gender, years of experience and years of experience squared.

Table B12. Broadband adoption and technological change: Levinsohn-Petrin

	2 skills	3 skills
	(1)	(2)
Intercept	4.225***	4.911***
	(0.535)	(0.505)
Capital	0.216***	0.236***
	(0.040)	(0.039)
Unskilled	0.537***	
	(0.0372)	
Low skilled		0.278***
		(0.0283)
Medium skilled		0.202***
		(0.0236)
Skilled	0.0328	0.0500**
	(0.0236)	(0.0241)
Availability ×		
Intercept	-0.0511	-0.300
	(0.497)	(0.404)
Capital	0.0110	0.00531
	(0.0251)	(0.0255)
Unskilled	-0.151***	
	(0.0530)	
Low skilled		-0.0830*
		(0.0426)
Medium skilled		-0.0188
		(0.0365)
Skilled	0.161***	0.127***
	(0.0365)	(0.0360)

* p < 0.10, ** < 0.05, *** p < 0.01.

Note: This table uses the survey sample of joint-stock firms. Sampling weights are used to ensure representative results for the population of joint-stock firms. (Un)Skilled comprises workers with(out) a college degree. The standard errors are clustered at the municipality level and robust to heteroskedasticity. All regressions include fixed effects for year, municipality and industry.

Table B13. Examples of workplace tasks

Task measures		
Routine	Abstract	Manual
Record-keeping	Forming/testing hypotheses	Picking/sorting
Calculation	Medical diagnosis	Repetitive assembly
Repetitive customer service (e.g., bank teller)	Legal writing	Janitorial services
	Persuading/selling	Truck driving
	Managing others	

Source: Autor, Levy, and Murnane (2003).

Appendix C: Placebo test

This appendix performs a placebo test, exploiting that under the exclusion restriction, there can be no intention-to-treat effect for firms that were not induced to adopt broadband because of the increase in availability.

Recall that $z_{mt} \in [0, 1]$ is a continuous measure of the availability rate to households in municipality m in year t. Our survey data shows that some firms had installed their own broadband networks prior to the rollout. In the terminology of Imbens and Angrist (1994), these firms are always takers, as they have adopted broadband even when $z_{kt} = 0$. By comparison, firms that do not adopt broadband internet even when $z_{kt} = 1$ are never takers.

In Table C1, we re-estimate model (1) on the subsample of always takers and never takers. A significant intention-to-treat effect on this subsample would be a violation of the exclusion restriction, that increased availabaility affects productivity and wages only through broadband adoption in firms, and not directly in any other way. By contrast, we find no significant relationship between labor productivity and availability rates among always and never takers, lending support to the exclusion restriction. In Table C2, we perform the same excercise for wages. Again, we find no evidence of a significant effect of availability rates on the subsample of workers in firms that are always takers or never takers.

Table C1. Placebo test: Output elasticities

	All	Always/never takers only
	(1)	(2)
Intercept	3.880***	5.096***
	(0.0965)	(0.809)
Capital	0.100***	0.114***
	(0.00495)	(0.0313)
Unskilled	0.576***	0.505***
	(0.0116)	(0.0869)
Skilled	0.136***	0.171***
	(0.00678)	(0.0295)
Availability ×		
Intercept	-0.500***	-0.212
	(0.111)	(0.709)
Capital	-0.00169	-0.0230
	(0.00750)	(0.0345)
Unskilled	-0.0226	0.0295
	(0.0234)	(0.0860)
Skilled	0.0755***	0.00944
	(0.0166)	(0.0278)
Observations	149,676	2,233

Note: The first column uses the population of joint-stock firms. The second column restricts the sample to firms that have adopted broadband even when the household availability rate is zero (always takers) and firms that have not adopted broadband even when the household availability rate is one (never takers). All regressions include fixed effects for year, industry and municipality. The standard errors are clustered at the municipality level and robust to heteroskedasticity.

Table C2. Placebo test: Labor outcomes

	Log hourly wage	
	All	Always/never takers only
	(1)	(2)
Unskilled	2.939***	2.916***
	(0.00455)	(0.0105)
Skilled	3.169***	3.171***
	(0.00420)	(0.0125)
Availability×		
Unskilled	-0.00622	0.0139
	(0.00455)	(0.0146)
Skilled	0.0178**	0.0135
	(0.00720)	(0.0188)
Observations	8,759,388	99,124

Note: In column 1, we consider workers aged 18-67 who are recorded in the wage statistics surveys. The second column restricts the sample to workers in firms that have adopted broadband even when the household availability rate is zero (always takers) and firms that have not adopted broadband even when the household availability rate is one (never takers). All regressions include fixed effects for year, industry and municipality. The standard errors are clustered at the municipality level and robust to heteroskedasticity.

Appendix D: Changes in marginal productivity vs. wages

To compare the changes in marginal productivity and wages, we rewrite the intention-to-treat model in equation (1) such that all variables are in levels. Abstracting from fixed effects and control variables, this equation corresponds to a Cobb-Douglas production function with exponents that potentially change with the availability of broadband internet:

$$Y_{imt} = e^{\alpha_0 + \alpha_1 z_{mt}} K_{imt}^{\delta_{k0} + z_{mt}\delta_{k1}} U_{imt}^{\delta_{u0} + z_{mt}\delta_{u1}} S_{imt}^{\delta_{s0} + z_{mt}\delta_{s1}}, \tag{6}$$

where Y_{imt} represents value added of firm i in municipality m in period t, K_{imt}, U_{imt} and S_{imt} are inputs of capital, unskilled, and skilled labor. In terms of equation (1), $(\alpha_0, \delta_{k0}, \delta_{s0}, \delta_{u0})$ is the coefficient vector δ_0, and $(\alpha_1, \delta_{k1}, \delta_{s1}, \delta_{u1})$ is the coefficient vector δ_1.

The marginal productivity of skilled labor is defined as

$$(\delta_{s0} + z_{mt}\delta_{s1}) \frac{Y_{imt}}{S_{imt}}$$

where $\delta_{s0} + z\delta_{s1}$ denotes the output elasticity of skilled labor.

To measure the pass-through, we compare a situation with no broadband availability ($z_{mt} = 0$) to a situation with full availability ($z_{mt} = 1$). In particular, we use the intention-to-treat effects on output elasticites and labor outcomes to compare the proportional change in the marginal productivity of skilled workers to the proportional change in the hourly wages of skilled workers. The latter is given directly from the intention-to-treat effects on wages. To compute the former, we use the estimates reported in Table 4 to calculate the predicted change in output elasticitiy of skilled labor and output Y_{imt}. To calculate the predicted change in the wage bills S_{imt}, we use the intention-to-treat effects on hourly wages and employment. In all calculations, we use the data on firms and workers in the population of joint-stock firms. Our calculation suggest that around 20 percent of the increase in marginal productivity of skilled workers is passed through to their wages. When we perform the same calculation for unskilled labor, we find an even smaller pass-through of changes in marginal productivity to wages.

Appendix E: Levinsohn Petrin approach

The system of equations given in (3) and (4) is used to estimate production functions where firms can change their technology by adopting broadband internet. To address the concern that the factor inputs in x_{imt} might be correlated with broadband adoption and unobserved productivity, we follow LP and take a more structural approach to address this threat to identifitcation of the production function.

LP use a structural model of an optimizing firm to derive the conditions under which intermediate inputs can be used to proxy for unobserved productivity in the production function. The error term ε_{imt} in (3) is assumed to be additively separable in a transmitted component (ω_{imt}) and an i.i.d. component (χ_{imt}). The key difference between ω_{imt} and χ_{imt} is that the former is a state variable, and therefore impacts the firm's decision rule, while the latter has no impact on the firm's decision. The intermediate input demand function depends on the firm-specific state variables, ω_{imt} and capital (k_{imt}),

$$a_{imt} = g_t(\omega_{imt}, k_{imt}). \tag{7}$$

and it must be monotonic in ω for all relevant k.[32] The monotonicity condition for intermediate inputs means that conditional on capital, profit maximizing behavior must lead more productive firms to use more intermediate inputs.

The monotonicity allows $g_t(\omega_{imt}, k_{imt})$ to be inverted to yield ω as a function of intermediate inputs and capital, $\omega_{imt} = \omega_t(a_{imt}, k_{imt})$. By expressing the unobserved productivity variable ω_{imt} as a function of observables, we are able to control for ω_{imt} in the second stage equation:

$$y_{imt} = x'_{imt}\beta_0 + D_{imt}x'_{imt}\beta_1 + w'_{imt}\theta + \lambda_m + \tau_t + \omega_t\left(a_{imt}, k_{imt}\right) + \chi_{imt}. \tag{8}$$

where β_0 is a vector consisting of $(\alpha_0, \beta_{k0}, \beta_{s0}, \beta_{u0})$, namely the pre roll-out intercept and output elasticities of capital, skilled labor, and unskilled labor. The vector β_1 is a vector consisting of $(\alpha_1, \beta_{k1}, \beta_{s1}, \beta_{u1})$ and measures the change in the intercept and the interaction effects between the input factors and broadband adoption. As in Olley and Pakes (1996) and LP, we use a polynomial expansion in a and k to approximate $\omega_t(\cdot)$. By simultaneous estimation of the first stage equations in (4) and the second stage equation in (8), we obtain consistent estimates of β_{u0}, β_{s0}, β_{k1}, β_{u1}, β_{s1}, and $\Phi_t\left(a_{imt}, k_{imt}\right) = \beta_{k0}k_{imt} + \omega_t(a_{imt}, k_{imt})$.

While these output elasticities are sufficient to assess how broadband adoption affects labor productivity, we need to identify β_{k0} to recover the full shift in production technology. Because k_{imt} is collinear with the non-parametric function $\omega_t(a_{imt}, k_{imt})$, further

[32] For simplicity, we assume as Olley and Pakes (1996) and Levinsohn and Petrin (2003) that capital is the only state variable over which the firm has control, while intermediates, labor and broadband internet are viewed as non-dynamic input factors.

assumptions are necessary.[33]

Assuming that ω_{imt} follows a first-order Markow process, we can write

$$\omega_{imt} = E\left[\omega_{imt}|\omega_{imt-1}\right] + \xi_{imt}.$$

This simply decomposes ω_{imt} into its conditional expectation at time $t-1$, $E\left[\omega_{imt}|\omega_{imt-1}\right]$, and a deviation from that expectation, ξ_{imt}. If the capital stock is pre-determined and current investment (which will react to productivity shocks) takes one period before it comes productive, it follows that

$$E\left[\xi_{imt} k_{imt}\right] = 0.$$

This is the moment which LP use to identify the capital coefficient. Roughly speaking, variation in k_{imt} conditional on ω_{imt-1} is the exogenous variation used for identification. To operationalize this approach in a GMM context, note that given a guess on the capital coefficient β_{k0}, we can rewrite unobserved productivity as

$$\omega_{imt}(\beta_{k0}) = \hat{\Phi}_{imt} - \beta_{k0} k_{imt}.$$

Given these $\omega_{imt}(\beta_{k0})$, we compute ξ_{imt} by non-parametrically regressing $\omega_{imt}(\beta_{k0})$'s on $\omega_{imt-1}(\beta_{k0})$'s and a constant term; we then form the residual

$$\xi_{imt}(\beta_{k0}) = \omega_{imt}(\beta_{k0}) - \hat{\Psi}\left(\omega_{imt-1}(\beta_{k0})\right)$$

where $\hat{\Psi}\left(\omega_{imt-1}(\beta_{k0})\right)$ are predicted values from the non-parametric regression.

The $\xi_{imt}(\beta_{k0})$'s are used to form a sample analogue to the above moment. i.e.

$$\frac{1}{T}\frac{1}{N}\sum_{t}\sum_{i}\xi_{imt}\left(\beta_{k0}\right)\cdot k_{imt}$$

where N denotes number of firms and T number of time periods. We estimate β_{k0} by minimizing the GMM criterion function

$$Q\left(\beta_{k0}\right) = \min_{\beta_{k0}}\left(\frac{1}{N}\frac{1}{T_{i1}}\sum_{i}\sum_{t=T_{i0}}^{T_{i1}}\xi_{imt}\left(\beta_{k0}\right)\cdot k_{imt}\right)^2$$

where i indexing firms and T_{i0} and T_{i1} index the second and last period in which firm i is observed.

Because our baseline sample is a repeated cross-section (rather than panel data), we adjust the above estimation procedure. Exploiting the random sampling of firms, we can

[33] β_{k1} is identified as the interaction of capital with D_{imt} provides independent variation. Note also that the intercept in the production function is not separately identified from the mean of $E\left[\omega_{imt}|\omega_{imt-1}\right]$ without some further restriction.

identify β_{k0} from the moment

$$E\left[\bar{\xi}_{mt}, \bar{k}_{mt}\right] = 0.$$

where the municipality average of a variable is denoted by upper bar. By applying the above procedure to our panel data at the municipality level, we obtain the GMM criterion function

$$Q\left(\beta_{k0}\right) = \min_{\beta_{k0}} \left(\frac{1}{M} \frac{1}{T_{m1}} \sum_{m} \sum_{t=T_{m0}}^{T_{m1}} \sqrt{N_{mt}} \bar{\xi}_{mt}\left(\beta_{k0}\right) \cdot \bar{k}_{mt} \right)^2$$

where T_{m0} and T_{m1} index the second and last period municipality m is observed and N_{mt} is the number of firms in municipality m in period t. To obtain standard errors on β_{k0}, we use bootstrap while clustering by municipality.