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Advanced Digital Technologies and Firm-Level Employment Outcomes

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Abstract

This paper investigates the effects of ultra-fast broadband (UBB) availability on firms' employment levels and their workforce composition. We utilize a unique and comprehensive municipality-level data set on the deployment of UBB connections in Italy, which began in 2015. By using information on firms' locations, we match this municipality-level data set with a rich administrative matched employer-employee balanced data set from 2012 to 2019. To address the endogeneity of UBB, we leverage the physical distance between each municipality and the nearest optical packet backbone node. Our instrumental variable regressions suggest a positive and significant effect of UBB on overall firm-level employment. When considering different categories of workers, by job contract type and the skill content of jobs, as well as the technological intensity of firms, we detect substantially differentiated UBB effects. We find complementarity effects of UBB with high-level jobs, particularly in the high-tech sector. Moreover, only for low-tech firms, we document a substitution effect of UBB with qualified blue-collar jobs.

Keywords: Ultra-fast broadband (UBB), fiber-based networks, firm-level employment, human capital, matched employer-employee data.

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1. Introduction

The roll-out of very high-speed broadband infrastructure has long been at the center of the attention of policymakers worldwide. In June 2023, the US announced the biggest investment in high-speed internet ever, to achieve the ambitious goal of whole speedy internet coverage by 2030. In Europe, the Commission reiterated its vision to turn Europe into a Gigabit Society by 2025, ensuring high-speed internet connections to all European households.¹ Many other countries, such as Australia,² Japan,³ Mexico⁴ and a multitude of African countries⁵ have also adopted national broadband plans to ensure the whole coverage of their territory.

Owing to their nature of general purpose technologies, very high-speed broadband connections have the potential to trigger economic growth on a massive scale and across different sectors (Bresnahan and Trajtenberg, 1995). The most recent UBB technology relies on fiber-based connections that allow a significantly higher performance compared to traditional copper-wire DSL connections, in terms of bandwidth, security, speed, reliability, signal strength, and cloud access.⁶ Such an increased capacity enables the transfer, processing, and storage of large amounts of data, ensuring substantial advantages in terms of productivity, innovation, competition, and security.

However, how these benefits may translate to the labor market is still an open question. Although higher productivity could result in higher wages and firm growth, firms might displace workers in response to the increased digitization enabled by UBB (Autor et al., 2020), and engage in significant (and structural) reallocations of their workforce, particularly in favor of skilled labor (Akerman et al., 2015). At the same time, if UBB increases digital competition (Cambini and Sabatino, 2023), some firms could undergo job destruction, thus negatively influencing workers' employment outcomes.

In this paper, we study the impact of fiber-based ultra-broadband (UBB) infrastructure on firms' employment in Italy, concentrating on the role of workers' skills and the technological content of firms' activities. Italy represents an interesting field experiment to evaluate the effects of UBB connections. Starting from 2015, massive investments have been made in UBB infrastructures, mostly driven by the national incumbent telecommunication op-

¹A Digital Agenda for Europe, European Commission, COM(2010) 245.

²The National Broadband Network April 2009, modified in 2013.

³E-Japan Strategy 2001.

⁴Mexican Digital Agenda 2011.

⁵National Information and Communication Technology Policy, final draft Nigeria, 2013; National Projects for Broadband Connectivity Burundi, 2011.

⁶See the TIM Netbook, 2018, available at https://rete.gruppotim.it/sites/default/files/download/TIMNetbook-FY2018-web_0.pdf

erator, TIM.⁷ Moreover, a new operator (OpenFiber) entered the market in 2017 and has significantly fostered UBB deployment.

We use uniquely rich administrative matched employer-employee balanced data on the whole population of private-sector firms in Italy over the period 2012-2019, matched with municipality-level information on the diffusion of UBB, which was introduced in Italy in 2015. The matched employer-employee data is provided by the Italian Social Security System (INPS). We focus on the entire population of private-sector firms with at least 10 employees (i.e., we do not consider micro enterprises). Our firm-level collapsed data set, on which we run the empirical analysis, consists of 747,184 firm-year observations. For each firm and year, we can identify all of its employees and observe several of their characteristics, including their job contract type, age, and wage, from which we retrieve information on their skill level. As regards UBB data, we use complete information provided by the only two broadband network operators in Italy on the staggered roll-out of UBB in each municipality, so that we observe the diffusion of UBB connections for each municipality and year. Finally, we retrieve other municipality-level information, which we use as controls in the econometric analysis, from the Italian Statistical Office (ISTAT).

Our empirical strategy is based on an event study design that exploits the staggered roll-out of UBB. Estimating the economic impact of broadband technologies is challenging, mainly due to the presence of unobservable economic factors contributing to the diffusion of such infrastructures (Cambini et al., 2023; Campante et al., 2017; Falck et al., 2014; Gavazza et al., 2018). Consistently with the endogenous relation between UBB roll-out and economic outcomes, we observe significant pre-trends before treatment. To identify causal effects, we use an instrumental variable (IV) approach that exploits plausibly exogenous variation in the distance between each municipality and its closest national optical packet backbone node (hereafter, we refer to it as “OPB node” or simply “node”; Cambini and Sabatino, 2023; Campante et al., 2017; Miner, 2015). These nodes are upgraded facilities of the old telephone communication network constructed around the early 2000s, hence their location can be considered exogenous to labor outcomes once we account for firm-level fixed effects and common time trends.

Our results from IV estimations show an overall positive impact of UBB on firm-level employment. The overall employment level is estimated to increase by 2.7% following the UBB roll-out. When considering different workforce categories, by job contract and workers’

⁷The Italian government refrained from universally funding UBB deployment due to EU State aid regulations (TFEU, art. 107). Instead, it directed public funds towards UBB investments exclusively in particular regions. These regions included rural areas and municipalities with sparse populations, where the incumbent telecommunications operator saw limited profitability in investing.

age, we find that the overall effect stems from the increase of middle managers and over-50 workers, thus suggesting a complementary effect of UBB with high-level, experienced job positions. When analyzing the moderating effect of firms' technological intensity, we find that this phenomenon is stronger in high-tech firms, where the number of middle managers is estimated to increase by 11% following UBB introduction, but is present also in low-tech firms (+3.4%). Finally, we dig into the categorization of workers according to their relative wage level, used as a proxy for skills. To this end, we identify, within each firm, high- and low-wage workers for each job contract type, by looking at their wage level relative to a narrowly defined reference cell. For high-tech companies, we confirm the presence of a strong complementary impact of UBB on high-level job positions, which emerges both in managerial roles (i.e., high-wage middle managers) and among highly specialized white-collar positions (i.e., high-wage white-collar workers). On low-tech firms, we confirm the presence of relatively more modest complementarity effects of UBB with high-level job positions as compared with high-tech companies. Finally, we do not detect substitution effects in high-tech sectors, whereas we observe the displacement of high-wage blue-collar workers, compatible with specialized manual jobs, among low-tech companies.

These results are consistent with the existence of a substantial skill-based digital divide (Akerman et al., 2015; Card and DiNardo, 2021; Goos et al., 2014; OECD, 2018), whereby firms tend to reconfigure their workforce in favor of employees that are more able to exploit the advantages offered by the digital revolution. Our results are also in line with those highlighted in the literature on ICT-induced labor market polarization (e.g., Autor et al., 2003). According to this literature, digital technologies tend to substitute workers in routine tasks entailing simple (cognitive or manual) activities that follow explicit rules. Such tasks (e.g. book-keeping, monitoring processes, processing information) are, in turn, concentrated in the middle of the wage distribution. Conversely, advanced ICT technologies complement workers in non-routine tasks involving problem-solving and complex communication activities. Non-routine tasks can either be associated with conceptual jobs at the top end of the wage distribution (e.g.: managerial and professional positions), or manual jobs at the bottom end of the distribution.

Most of the available studies on the effects of broadband technologies in the labor market focus on basic broadband technologies (i.e., ADSL connections), finding positive impacts on wages and employment, but only for specific types of workers or areas (Forman et al., 2012; Akerman et al., 2015; Czernich et al., 2011). This literature highlights the presence of complementarities between basic broadband technologies and workers' skills (Akerman et al., 2015), with effects that are typically concentrated in high-income regions and IT-intensive sectors (Forman et al., 2012). The skill-bias induced by the technological change might

depend on job tasks. ICT investments have been found to increase the earnings and employment of workers engaged in abstract tasks (Falck et al., 2021), because they cause a shift away from routine tasks –more amenable to automation–toward problem-solving and complex communication tasks –nonroutine abstract tasks (Autor et al., 2003)–. Indeed, Gaggli and Wright (2017) find that higher ICT skills increase the abstract task content of jobs and decrease their routine and manual task content, suggesting that advanced digital technologies might raise the employment of workers in top-level (managerial) positions, especially in sectors where higher digital skills are necessary, i.e. high-tech sectors.

The economic literature focusing on high-speed broadband is scant, and mostly based on aggregated data at a country or regional level (Briglaue and Gugler, 2019; Briglaue et al., 2021; see also the survey by Abrardi and Cambini, 2019). At a micro-level, UBB seems to have a positive impact on firms’ productivity (Cambini et al., 2023) and economic resilience to negative economic shocks (Abrardi and Sabatino, 2023). However, the effects on the labor market are more nuanced due to the presence of substantial heterogeneities within worker categories (Abrardi et al., 2023). Hasbi and Bohlin (2022), exploiting data from measurement tests realized by Internet users in Sweden, highlights a complementary effect of UBB quality with high-skill jobs and a substitution effect of low-skilled jobs, although these effects are heterogeneous across different municipality sizes. Also in rural areas, broadband coverage has a significant positive effect only on highly-qualified jobs (Briglaue et al., 2019) and on business startups in areas with favorable economic, natural, and demographic conditions (Duvivier and Bussire, 2022). In New Zealand, Fabling and Grimes (2016) find a significant impact of UBB on employment only for companies that make complementary investments in organizational capital. Overall, these results point to the presence complementarities between UBB, human capital, and general economic conditions, suggesting a role for UBB in expanding high-income cognitive jobs. Further research has analyzed the impact of UBB on business creation, finding that higher broadband speed levels may affect self-employment (Abrardi et al., 2023), entrepreneurship and firms’ location decisions (Canzian et al., 2019; Duvivier, 2019), although company creation also seems to be affected by important complementarities with industry types and educational levels (Hasbi, 2020). Indeed, UBB seems to increase firm entry only in large urban centers and digital-intensive sectors with a highly skilled workforce (Duvivier et al., 2021; Cambini and Sabatino, 2023), whereas it increases net exit in sectors with low digital skills, such as Hotels, Restaurants, and Trade (Cambini and Sabatino, 2023). In Italy, access to UBB has spurred self-employment in urban areas, in municipalities at the top quartile of labor income and where the population has a higher level of education, although UBB has also enabled necessity-based self-employment in low-income municipalities (Abrardi et al., 2023).

We contribute to the literature by providing the first quantitative evidence based on large micro data on the impact of last-generation broadband infrastructure on firms’ employment levels, specifically analyzing the role of complementary and substitute factors such as workers’ skills and the technological intensity of sectors.

The rest of the paper is organized as follows. Section 2 provides information on the deployment of the UBB infrastructure in Italy and introduces the data. Section 3 describes the empirical model and the identification strategy. Section 4 discusses the results. Finally, Section 5 concludes.

2. Data

2.1. Matched employer-employee data

We gather information on firms and their workers from a uniquely rich yearly administrative matched employer-employee data set on the entire population of private-sector Italian firms provided by INPS. In our empirical analysis, we focus on the balanced panel of firms employing 10 workers or more (i.e., we exclude micro firms) over the period 2012-2019. The INPS data include rich information on workers’, jobs’ and firms’ characteristics. This data set is composed of three parts. The first part is the so-called “worker archive”, which collects personal information pertaining to a worker (e.g., age). The second part is the “job archive”, which collects data on the workers’ yearly gross earnings, number of days worked over the calendar year, job contract type (e.g., blue-collar worker, white-collar worker, middle manager, top manager), and contract duration (i.e., fixed-term *versus* open-end worker). Finally, there is the “firm archive”, which provides information about the firm, including its location, establishment date, and sector of activity.

Starting from the worker-level information, for each firm and year, we compute the total number of employees. This is the main dependent variable, through which we empirically explore whether and in which way UBB connections impact a firm’s employment level. As discussed below, in the empirical analysis, we consider the number of employees in logarithm to explore semi-elasticities, $\log(\text{employees}_{i,m,t})$, where i indicates the firm, m the municipality in which it is located, and t is the year.

We then compute several workforce characteristics for each firm and year, to be used as additional dependent variables. Such variables include the number of workers by age category as well as by job contract type. Concerning the first set of variables, we compute the numbers of workers under 29, between 30 and 49, and over 50 years of age. As regards the second set of variables, that is, by job contract, we compute the numbers of blue-collar and white-collar workers, the number of middle managers, and the number of top managers.

All of these variables are used in the empirical analysis in logarithms to explore the impact of UBB on the employment of workers by age and contract type groups in the firms.

Finally, we compute the number of employees for each firm and year by looking at their relative wage levels, in order to measure the skill content of each worker and, on aggregate, of the firms' employees. To this end, we identify the so-called "high-wage workers" and "low-wage workers" with respect to a reference cell. We first compute the distribution of contractual daily wages for each year, administrative province, sector (ATECO 2007, 2-digit level), firm size (i.e., small, medium-sized, and large firms), job contract (e.g., blue-collar workers, white-collar workers, etc.), age class (i.e., under 29, between 30-49, and over 50 years), temporary *versus* open-end status, and part-time *versus* full-time status. Hence, the reference cell is rather narrow, accounting for multiple sources of heterogeneities in the wage-setting process. For each worker, we then attach the label "high-wage" if his/her daily wage is equal to or above the 75th percentile of the corresponding daily wage distribution defined at the cell level. On the contrary, we define a worker to be "low-wage" if his/her daily wage is equal to or below the 25th percentile of the corresponding cell. It is important to stress that this classification, among the other aspects (e.g., sector, firm size, location, etc.) is specific to each job contract since the reference cell is defined also at this particular level. For example, the wage of a blue-collar worker in a firm is confronted with the wages of the blue-collar workers in the reference cell, that is, working within the same sector and location, in firms with a similar size, of a similar age category, job contract duration, and job contract working hours. Finally, for each firm and year, we compute the number of the so-defined "high-wage" and "low-wage" workers by simply counting the workers in each of these two categories, separately for each job position. We thus compute the number of high-wage and low-wage blue-collar workers, the number of high-wage and low-wage white-collar workers, the number of high-wage and low-wage middle managers, and, finally, the number of high-wage and low-wage top managers. As before, all of these variables are used as dependent variables and inserted in the regressions in logarithms.⁸

2.2. UBB data, background, and the merging process

Our UBB data come from two sources. First, we have access to municipality-level data provided by the Italian incumbent operator, Telecom Italia Mobile (TIM), on the staggered UBB roll-out of this operator since the introduction of UBB in Italy in 2015. The second

⁸Note that we can precisely measure a worker's contractual daily wage in each year, by dividing his/her yearly gross earnings with the full-time equivalent number of days worked. We know the exact proportion of days of work stipulated in each part-time contract compared with the corresponding full-time contract. This information was obtained from the INPS variable called "settimane utili".

data source comes from OpenFiber, the only alternative UBB operator, which entered the market in 2017, and collects additional information on the municipalities covered by such operator. Using these data, we thus have a comprehensive record of which municipalities have access to UBB connections (either provided by TIM or OpenFiber) for each year of observation, from 2015 to 2019.

The rollout of UBB in Italian municipalities commenced in 2015 as a result of the implementation of the Italian Strategy for High-Speed Broadband, aligning with the primary objectives of the 2020 Digital Agenda for Europe.⁹ The UBB deployment plan has been executed through a combination of public and private investments. As previously mentioned, only two distinct networks provide UBB services to end consumers. The first one is owned by the telecommunication incumbent TIM, which leverages pre-existing telecommunication facilities originally used for voice telephone and ADSL connections. Consequently, TIM has been the first to invest in UBB infrastructures throughout Italy since 2015, covering the vast majority of municipalities with a mix of full-fiber (FTTH) and copper-fiber (FTTC) connections. The second network is owned by OpenFiber, a wholesale operator currently under the ownership of Cassa Depositi e Prestiti, the investment branch of the Italian Ministry of Treasury, in conjunction with two international private investment funds. OpenFiber entered the market in 2017 by acquiring Metroweb, a private telecom company covering a few large cities (e.g., Milan and Turin). Since then, OpenFiber has invested in FTTH connections mainly in large cities, as well as in less densely populated areas (the so-called “white areas”), after being the recipient of public resources awarded through competitive procedures run by the Italian Government. By the end of 2019, OpenFiber covered 392 municipalities, 261 of which were also (fully or partially) covered by TIM.¹⁰ Figure 1 illustrates the proliferation of UBB in Italy. As depicted in the figure, as of the conclusion of 2019, approximately 55% of Italian municipalities provided UBB services with connection speeds surpassing 30 Mbps, encompassing roughly 90% of the Italian population. In contrast, ADSL connections have reached a mature phase, with nearly all municipalities and their respective populations having access to these basic connections.

Our primary regressor of interest, $UBB_{m,t}$, is an indicator variable that takes a value of one if municipality m has access to UBB connections in year t , and zero otherwise.¹¹ It

⁹The Digital Agenda for Europe specifies the goals in terms of network coverage and service adoption for the whole European population. See <https://www.europarl.europa.eu/factsheets/en/sheet/64/digital-agenda-for-europe> for more information.

¹⁰OpenFiber’s deployment plan can be found here: <https://openfiber.it/area-infratel/piano-copertura/>.

¹¹This indicator is approximately equivalent to the UBB coverage rate within the municipality. Refer to Figure A.1 in Appendix A for a visual representation of the discontinuous change in the UBB coverage rate

is important to note that our UBB indicator specifically refers to the availability of these connections within a municipality in a given year. One notable concern regarding this indicator is whether the spread of UBB is associated with its adoption by Italian firms. The evolution of UBB subscriptions for both households and businesses from 2015 to 2019 is depicted in Figure A.2 in Appendix A. In line with the findings of Akerman et al. (2015), we observe a substantial correlation between UBB usage in households and firms, suggesting that our municipality-level UBB deployment data effectively serve as a proxy for the availability of UBB connections to businesses.

Furthermore, we have access to information regarding the incumbent’s telecommunication infrastructure, which comprises components operating at both national and local levels. On a national scale, data transmission flows through the backbone, where various nodes are interconnected *via* optical fiber connections. At the local level, traffic is then routed towards the local central offices, from which the “last mile” connection originates, establishing the link between the service provider and end-users. It is important to note that both the nodes and local central offices are pre-existing facilities from the old telephone network, established well before the introduction of UBB.¹² From this information, we construct a critical part of our instrumental variable, OPB_m , which defines the distance (in kilometers) between each municipality and the closest node (see the discussion in Section 3).

Finally, we obtain municipality-level information from the Italian Statistical Institute (ISTAT). These variables, used as controls in the regressions, include, among others, the current population in municipality m in year t and the total area of the municipality (this last piece of information is obtained from the 2011 Italian Census).

We merge the collapsed INPS firm-level data with the municipality-level UBB (and ISTAT) data by utilizing the information provided by INPS on the firms’ municipalities. In essence, we observe whether each firm is situated in a municipality with UBB connectivity or not at each time point. Our final merged dataset encompasses 747,184 firm-year observations, for a total of 93,398 firms.

2.3. Descriptive statistics

Table 2 provides a comprehensive summary of our final data set. The average firm size is relatively modest, with approximately 66 employees, which aligns with the prevalence of small and medium-sized enterprises in the Italian industrial landscape. Furthermore, the median employee count stands at 22, indicating that half of the firms in the sample fall

within municipalities, with a sharp increase to nearly one when UFB is introduced in the municipality.

¹²For instance, the nodes were established between 2001 and 2005, and the construction of local central offices dates back even further.

into the category of small-sized establishments. We observe that 49.7% of our firm-year observations are covered with UBB connections. However, if we only consider the years following the UBB roll-out, such a percentage increases to 79.6%. The firms in our data set exhibit an average age of approximately 22 years. In terms of sectoral distribution, 37.5% of these firms operate within the manufacturing sector, while 5.5% are engaged in the construction industry. Additionally, 17.4% and 38% are associated with the trade and services sectors, respectively, with a smaller fraction operating in the mining and quarrying or utilities sectors. Geographically, about one-third of the firms are situated in the North-West of Italy (34.6%), while 28.4% are located in the North-East. Furthermore, 17.9% and 19.1% originate from the Center and South/Islands macro-areas, respectively. In terms of technological intensity, 24.9% of the sample comprises high-tech firms, while the remaining 75.1% consists of low-tech entities.¹³

Table 3 provides a comprehensive breakdown of the workforce composition within the firms under analysis. In particular, it provides descriptive statistics concerning the number (and shares) of workers classified by job contract type, including blue-collar workers, white-collar workers, middle managers, and top managers. It further dissects the workforce by age, categorizing employees into three distinct groups: young (under 29 years old), middle-aged (between 30 and 49 years old), and older workers (over 50 years of age). Finally, the table offers information regarding the number and proportional representation of workers

¹³For manufacturing firms, we have identified high-tech companies using the classification criteria recommended by the OECD. This classification relies on R&D intensities and encompasses the following sectors: manufacture of basic pharmaceutical products and preparations; manufacture of computers and electronic and optical products; electro-medical equipment, measurement instruments, and clocks; manufacture of chemical products; manufacture of electrical equipment and non-electric household appliances; manufacture of machinery and equipment not elsewhere classified; manufacture of motor vehicles, trailers, and semi-trailers; manufacture of other transport equipment. A comprehensive OECD document detailing this classification can be accessed at <https://www.oecd.org/sti/ind/48350231.pdf>. For firms operating in the services sector, which also includes trade, we have identified high-tech companies based on the Knowledge Intensive Activities (KIA) classification. This encompasses the following sectors: maritime and waterway transport; air transport; publishing activities; film, video, and television program production, music and sound recording activities; programming and broadcasting activities; telecommunications; software development, computer consultancy, and related activities; information service activities and other information technology services; financial service activities (excluding insurance and pension funding); insurance, reinsurance, and pension funding (excluding mandatory social insurance); auxiliary financial and insurance services; legal and accounting activities; management consultancy and management activities; architectural and engineering activities; testing and technical analysis; scientific research and development; advertising and market research; other professional, scientific, and technical activities; veterinary services; employment placement and provision of personnel services; security and investigation services; education; human health activities; residential care social work activities; non-residential social work activities; creative, arts, and entertainment activities; library, archives, museums, and other cultural activities; gambling and betting activities; sports, entertainment, and recreation activities. Note that the high-tech and low-tech subdivision is not defined for mining and quarrying activities, utilities, and constructions.

based on their relative wage levels. These categories are defined as “high-wage” and “low-wage” workers, as outlined in Subsection 2.1. The table, and particularly the information on workers’ shares, reveals that a substantial proportion of the average firm’s workforce comprises blue-collar workers, constituting 56.5% of the total. White-collar workers also make up a significant portion, accounting for 35.8%. In contrast, managers, both at middle and top positions, collectively represent a relatively modest share, approximately 2.7% of the average firm’s workforce. In terms of age demographics, a substantial portion of the workforce in the average firm falls within the prime-age category (58%), indicating that individuals between the ages of 30 and 49 constitute the core working population. Conversely, younger and older workers constitute smaller percentages of the workforce, with young workers (under 29) comprising 16.5% and older workers (over 50) making up 25.5% of the total.

3. Empirical strategy

3.1. Empirical model

In our empirical analysis, we explore the impact of UBB access on firm-level employment. Our baseline model takes the following form:

$$\ln(\text{employees})_{i,m,t} = \alpha + \beta UBB_{m,t} + \theta X_{m,t} + \tau_t + \eta_i + \epsilon_{i,m,t}. \quad (1)$$

The dependent variable is the natural logarithm of the number of workers employed by firm i , located in municipality m , and year t . Our variable of interest is $UBB_{m,t}$, which identifies municipalities with access to UBB connections. The $X_{m,t}$ vector collects municipality-level controls. It collects baseline municipality characteristics interacted with year dummies, so as to control very flexibly for heterogeneity in the evolution of firm employment based on pre-UBB municipality characteristics.¹⁴ These characteristics include municipality population, aggregate GDP, total area (5 classes), together with information on the workforce composition of the firms in the municipality. The term τ_t collects region-year fixed effects, while η_i denotes firm-specific fixed effects. Finally, $\epsilon_{i,m,t}$ is a mean-zero error term. Throughout the analysis, we cluster standard errors at the municipality level, thereby allowing for serial correlation within each municipality.

The empirical model described in Equation (1) resembles an intention-to-treat analysis, such as the one in Akerman et al. (2015), where the staggered roll-out of UBB coincides with the intention-to-treat assignment. The identification of the causal impact of UBB on firm

¹⁴This is particularly relevant in our IV approach, since we have to ensure that the instrument does not correlate with any underlying trends that might affect firm productivity (see the discussion in Subsection 3.2).

productivity requires such an assignment to be as-good-as-random, conditional on observables. In other words, UBB should be uncorrelated with the error term $u_{i,m,t}$, conditional on the firm- and municipality-level controls included in Equation (1). Although our fixed effects estimation allows us to control for time-invariant firm-level unobservables, other time-varying firm- or municipality-level shocks may correlate with UBB roll-out, thus implying that the estimate of the coefficient of interest may be confounded by such an omitted variable bias.

3.2. IV approach

We deal with the endogeneity of UBB diffusion through an IV approach, which exploits the incumbent’s upstream telecommunication infrastructure. In particular, our IV leverages on the geographical location of the incumbent’s OPB nodes.¹⁵ We compute the distance, in kilometers, from the closest node for each municipality (OPB_m) and we interact it with a $Post_{2015}$ dummy, which takes the value of one from the year of UBB introduction onward. This instrument is relevant in explaining UBB roll-out because UBB is first introduced in locations relatively closer to the nodes. This is strictly linked to the positioning of a critical UBB input called Optical Line Terminals (OLTs). That is, UBB is first introduced in locations relatively closer to nodes because, in turn, OLTs are first installed near the nodes. Figure 2 shows the relationship between the distance from the closest node (i.e., OPB_m) and both UBB and OLT diffusions, in 2015, when UBB was introduced, and 2019, our last year of observation. As can be seen from the figure, there is a substantial negative relationship between OPB_m and the OLT diffusion, which, in turn, drives the UBB roll-out, thus implying that municipalities relatively closer to nodes are indeed more likely to receive UBB.

Our exclusion restriction assumption is that, whatever correlation exists between firm employment and the distance of the municipality from the closest node, such a correlation is constant around the introduction of UBB. This assumption could be violated by the existence of underlying municipality-level trends correlated with both our instrument and employment. For instance, firms located farther away from the nodes may have a different growth than those firms relatively closer to them, for reasons that are unrelated to the UBB roll-out. Therefore, we also control for differential trends in our IV estimates on the basis of the baseline municipality characteristics discussed before (see Cambini and Sabatino, 2023; Campante et al., 2017, for a similar empirical strategy).

¹⁵Figure 3 depicts the location of the 35 nodes of the incumbent’s telecommunication network.

4. Results and discussion

4.1. The impact of UBB on overall employment

Table 4 collects the main results concerning the impact of UBB on overall firm-level employment.

In Columns (1)-(4), the table reports three sets of OLS estimates of Equation (1) and one set of the IV-2SLS estimates. All of these estimates account for firm fixed effects. They further control for firm age and size dummies, the sector of economic activity of the firm (at the ATECO 2007 3-digit level), as well as for year-region interaction dummies. The first OLS specification (OLS1) only includes the aforementioned controls. The second OLS regression (OLS2) adds municipality-level controls for the population of the municipality and its GDP at the 2012 baseline year, as well as its geographic extension (5 classes, obtained from the 2011 Italian census). The third OLS regression (OLS3) comprises additional municipality-level controls pertaining to the average workforce composition of the firms within the municipality. These controls include (i) the average firm-level shares of blue-collar workers, white-collar workers, and managers (both middle and top managers) in the municipality, (ii) the average firm-level shares of under-29 workers, workers aged between 30 and 49 years, and over-50 workers in the municipality, (iii) the average firm-level shares of temporary workers in the municipality. The controls in (i), (ii), and (iii) are all computed at the baseline year 2012. All these municipality-level controls at the baseline year in OLS2 and OLS3 are then interacted with year dummies. The IV specification (IV1) starts from Specification OLS3 and instruments the presence of UBB with our $Post_{2015} \times OPB_m$ instrument, as discussed in Section 3. In all the regressions of the paper, the standard errors are clustered at the municipality level.

Focusing on the OLS estimates, that is, Columns (1)-(3) of Table 4, we observe small, either negative or positive, and not statistically significant coefficients associated with UBB. We have run the event study regressions relative to these three OLS specifications. We found strong pre-trends, which invalidate such estimates, pointing to the presence of substantial endogeneity and the need for IV estimation.¹⁶

Moving to our IV results, in Column (4), the estimated coefficient associated with UBB rises, turning positive, and becomes statistically significant. The estimated impact of UBB on firm-level employment is +2.7%.

Table 5 presents the first-stage results of our IV estimates. The coefficient associated with the instrument (i.e., $Post_{2015} \times OPB_m$) is negative and significant at the 1% level, thus indicating a negative correlation between the distance from the OPB node and the availability

¹⁶Results of these estimates are available from the authors upon request.

of UBB connections, which resists the numerous controls inserted in the regression. The first-stage F-test statistic is well above the conventionally acceptable threshold levels, thus indicating that the instrument is powerful (equal to 84.35).

In sum, up to now, we found that UBB connections have a positive effect on firm-level employment, thereby increasing the average firm size. However, is this effect common to all the workforce in the firm or are there differentiated effects based on relevant workers' characteristics, such as their job contract, age, and skill content? And, are these potentially heterogeneous effects differentiated depending on the technological intensity of the firm's activities? We investigate these questions in the following subsection.

4.2. The role of job contract type, workers' age, skills, and technological intensity

In this subsection, we explore potential sources of heterogeneity in the impact of UBB on different types of employment and based on different firms' technological intensity levels.

First, we look at the impact of UBB on firm-level employment subdivided by type of job contract and workers' age class. We report these results in Table 6. For these, and the following results, we show IV estimates (i.e., Specification IV1 of Table 4).

As concerns the job contract, we consider four different dependent variables, that is, the number, in firm i and year t , of blue-collar workers, white-collar workers, middle managers, and top managers, always expressed in logarithms. For workers' age, we consider three different dependent variables, one for each age class. We thus have the numbers, in firm i and year t , of workers under 29, between 30 and 49, and over 50 years of age, all expressed in logarithms. Therefore, the resulting regressions estimate the impacts of UBB on the firm-level employment of each of these categories of workers.

By looking at Table 6, we can see that the detected overall positive impact is not generalized to all workforce categories, but stems from particular workers' typologies. According to our estimates, firms substantially increase the employment of middle managers (+5.2%) and over-50 workers (+9.9%) following the introduction of UBB, both coefficients being significant at the 1% level. On the contrary, the employment of other typologies of workers is estimated not to be affected by the introduction of UBB, as shown by the typically lower and not significant coefficients associated with UBB in such regressions.

This initial set of findings thus indicates that UBB has differentiated effects on the employment of workers, contingent upon their job contract and age. Fast internet connections appear to result in heightened employment levels in managerial roles, demanding more seasoned professionals. It thus seems that UBB has a complementary effect on high-level positions, while we do not detect any substitution effect with low-level job positions.

Another important question is whether these heterogeneous effects are differentiated de-

pending on the degree of technological intensity of the sector in which the firm operates. We answer this question by re-estimating the regressions in Table 6 separately for high-tech and low-tech companies. Subsection 2.3 reports the detailed list of high-tech sectors. We show the results of this analysis in Table 7. The first column of the table refers to high-tech firms, whereas the second column is for low-tech firms. As usual, we report the IV results.

As can be seen from the table, the impact of UBB on high-level employment detected in Table 6 is predominant in high-tech industries. However, it is also discernible, albeit with a lesser degree of impact, in low-tech sectors. Specifically, within high-tech enterprises, UBB is projected to yield an 11% rise in the number of middle managers employed within the average firm, along with a 12.2% increase in the number of workers aged over 50, both coefficients statistically significant at the 1% level. Conversely, in low-tech firms, we observe an increase of 3.4% for middle managers and 8.2% for workers aged over 50 as a result of UBB introduction. Interestingly, among low-tech firms, we detect a mildly negative effect stemming from UBB roll-out for blue-collar workers (-3.3% , significant at the 10% level).

Overall, these results give an affirmative answer to our question: the technological intensity of the firm is an important dimension of differentiation. The positive impact on high-level positions emerges more strongly in advanced high-tech sectors, thus suggesting that the complementary effect of UBB on managerial positions increases together with the technological content of the firm’s activities. Together with a reduced complementary relationship with high-level positions, for low-tech firms, we also detect possible substitution effects of UBB with low-level positions (i.e., blue-collar jobs).

Another important question has to do with the skill content of jobs. Up to now, we have found differentiated impacts of UBB by job contract and workers’ age and, further, based on firms’ technological intensity. However, within the different job categories, which type of workers are impacted the most? Those who are relatively more or less skilled? To answer this question, we use the categorization of a firm’s workers according to their relative wage level, used as a proxy for skills. As described in Section 2, we identify, within each firm, high- and low-wage workers for each job contract type, by looking at their wage level relative to a narrowly defined reference cell. In Table 8, we thus estimate, with Specification IV1, the impact of UBB roll-out on each of the resulting eight firm-level categories of workers, that is, high- and low-wage blue-collar workers, white-collar workers, middle managers, and top managers (all expressed in logarithm). Note that this table, like Table 7, differentiates between high- and low-tech firms. The first column of the table reports the results for high-tech firms, whereas the second column refers to low-tech companies.¹⁷

¹⁷As discussed in Section 2, the high- and low-wage categories of workers are defined with reference to the

First, for high-tech firms, we can see that the detected positive impact of UBB roll-out on middle managers is concentrated on high-wage rather than low-wage middle managers. The estimates predict a +4.4% increase in high-wage middle managers following the introduction of UBB. Interestingly, we also detect a strong positive impact also for high-wage white-collar workers (+11.1%), which did not emerge for white-collar workers overall. High-wage white-collar workers are compatible with specialized technicians and professionals. This evidence further points to the presence of a strong complementary impact of UBB on high-level job positions in high-tech firms, both in managerial roles (middle managers) and among highly specialized positions (high-wage white-collar workers).

Among low-tech firms, we discover a somewhat differentiated pattern. First, we find that the detected positive impact on middle managers here emerges, with a relatively low magnitude, on low- and not high-wage middle managers, the former increasing by +2% as a result of UBB introduction. Second, we find, as for high-tech companies, evidence of a positive impact of UBB on high-wage white-collar workers, though substantially lower in magnitude as compared with high-tech firms (+4.7%). Third, we find that the documented negative impact on blue-collar workers emerging in low-tech firms stems from high-wage blue-collar workers (−5%), compatible with specialized blue-collar jobs. Low-wage blue-collar workers, compatible with elementary occupations such as warehouse workers and cleaning staff, are instead estimated not to be affected by UBB introduction. On the one hand, these results further indicate that low-tech firms undergo relatively more modest complementarity effects of UBB with high-level job positions as compared with high-tech companies. On the other hand, they suggest that low-tech firms are faced with displacement of specialized blue-collar job positions, highlighting the presence of substitution effects among such roles.

5. Conclusions

In this paper, we explored the impact of advanced information and communication technologies on firm-level employment outcomes. We leveraged a uniquely rich balanced panel data set, which collects municipality-level information on ultra-fast broadband access merged with administrative matched employer-employee data on the population of Italian private-sector firms with at least 10 employees. Our empirical strategy exploited the relative distance between each municipality and the closest backbone node as a source of plausibly exogenous variation.

75th and 25th percentiles of the relative cell’s wage distribution, respectively. Therefore, this categorization excludes workers lying between the 25th and the 75th percentiles. This is done in order to more neatly reflect low- and high-skilled workers. Therefore, the results in Table 8 are not directly comparable with those reported in Table 7.

The results obtained from instrumental variable estimations demonstrate an overall positive impact of UBB on employment at the firm level. Following the implementation of UBB, we estimate a 2.7% increase in overall firm-level employment. Upon examining the impact across various workforce categories, such as by job contract, workers' age group, and skill content of jobs, we find substantially differentiated effects of UBB. In short, for high-tech companies, our findings reveal a robust complementary impact of UBB on high-level job positions, observed in both managerial roles (i.e., high-wage middle managers) and highly specialized white-collar positions (i.e., high-wage white-collar workers). In contrast, for low-tech firms, the complementarity effects of UBB with high-level job positions are relatively more modest compared to high-tech companies. Notably, no substitution effects are detected in high-tech sectors, whereas the displacement of high-wage blue-collar workers, consistent with specialized manual jobs, is observed among low-tech companies.

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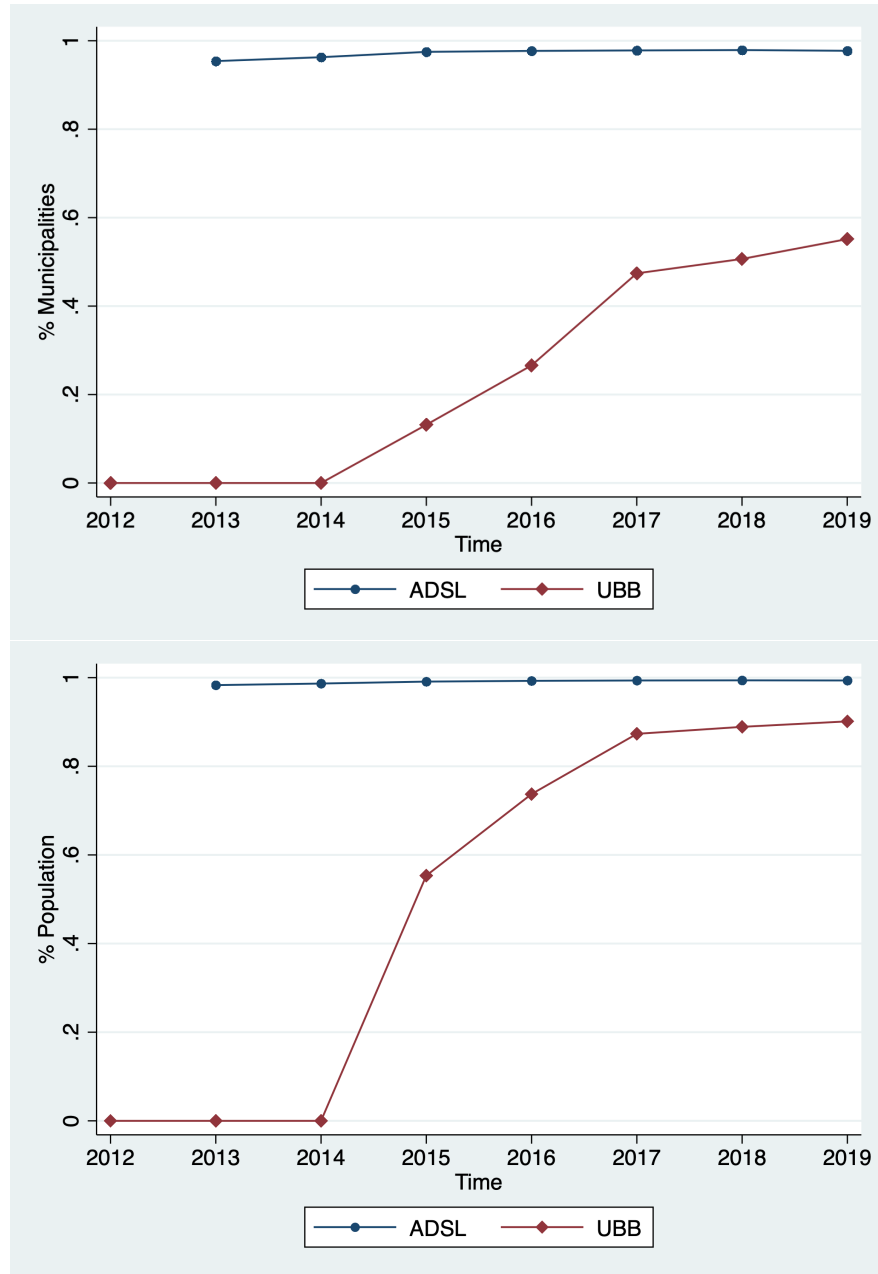
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Table 1: **Broadband technologies and variables: acronyms and descriptions**

ADSL	Asymmetric digital subscriber line	Broadband technology in which the “last mile” is made of copper wires derived from the old telephone communication network. It allows a maximum speed of 7Mbps in download.
UBB	Ultra-fast broadband	Broadband technology based on optical fiber cables in the “last mile”. It includes both FTTC and FTTH connections, allowing a speed between 30Mbps and 1 Gbps in download.
FTTC	Fiber-to-the-cabinet	Networks that involve a first segment of optical fiber cables from the local central office to a cabinet near the customers’ premises and then a final segment of copper wire from the cabinet to the final customers. They allow a speed between 30Mbps and 100Mbps in download.
FTTH	Fiber-to-the-home	Networks in which the “last mile” is made of optical fiber cables, from the local central offices to the customers’ premises. They allow the maximum speed of 1Gbps in download.
OPB	Optical packet backbone	It refers to the national backbone of the incumbent’s telecommunication infrastructure. It comprises 35 nodes, which are upgraded facilities of the old telephone communication network constructed around the early 2000s.
OLT	Optical line terminal	A specific device that converts optical signals and enables the supply of UBB to final customers. It acts as an endpoint device in a passive optical network.
$UBB_{m,t}$		Indicator that takes a value of one if municipality m has access to UBB at time t , and zero otherwise.
OPB_m		Variable that defines the distance (in kilometers) between municipality m and the closest OPB node.

Figure 1: **UBB diffusion**



Source: UBB (2012-2019).

Table 1 reports the list of broadband acronyms and variables, with related descriptions.

Table 2: Sample summary statistics: UBB and general firm characteristics

Variable	Mean or %	Std. dev.	25th ptc.	Median	75th ptc.
$UBB_{m,t}$ (%)	49.7	-	-	-	-
OPB_m (km)	26.325	24.542	8.001	21.068	39.437
Employees	66.298	676.601	15	22	43
Firm age (years)	21.762	13.423	11	19	31
High-tech (%)	24.9	-	-	-	-
Low-tech (%)	75.1	-	-	-	-
Small (10-49 employees)	78.9	-	-	-	-
Medium-sized (50-249 employees)	17.9	-	-	-	-
Large (over 249 employees)	3.2	-	-	-	-
Mining and quarrying (%)	0.3	-	-	-	-
Manufacturing (%)	37.5	-	-	-	-
Construction (%)	5.5	-	-	-	-
Utilities (%)	1.3	-	-	-	-
Trade (%)	17.4	-	-	-	-
Services (%)	38.0	-	-	-	-
North-West (%)	34.6	-	-	-	-
North-East (%)	28.4	-	-	-	-
Center (%)	17.9	-	-	-	-
South and Islands (%)	19.1	-	-	-	-
Observations: 747,184					

Source: UBB-INPS data set (2012-2019).

Table 1 reports the list of broadband acronyms and variables, with related descriptions. “Employees” is the number of employees in the firm. For manufacturing firms, we have identified high-tech companies using the classification criteria recommended by the OECD. This classification relies on R&D intensities and encompasses the following sectors: manufacture of basic pharmaceutical products and preparations; manufacture of computers and electronic and optical products; electro-medical equipment, measurement instruments, and clocks; manufacture of chemical products; manufacture of electrical equipment and non-electric household appliances; manufacture of machinery and equipment not elsewhere classified; manufacture of motor vehicles, trailers, and semi-trailers; manufacture of other transport equipment. For firms operating in the services sector, which also includes trade, we have identified high-tech companies based on the Knowledge Intensive Activities (KIA) classification. This encompasses the following sectors: maritime and waterway transport; air transport; publishing activities; film, video, and television program production, music and sound recording activities; programming and broadcasting activities; telecommunications; software development, computer consultancy, and related activities; information service activities and other information technology services; financial service activities (excluding insurance and pension funding); insurance, reinsurance, and pension funding (excluding mandatory social insurance); auxiliary financial and insurance services; legal and accounting activities; management consultancy and management activities; architectural and engineering activities; testing and technical analysis; scientific research and development; advertising and market research; other professional, scientific, and technical activities; veterinary services; employment placement and provision of personnel services; security and investigation services; education; human health activities; residential care social work activities; non-residential social work activities; creative, arts, and entertainment activities; library, archives, museums, and other cultural activities; gambling and betting activities; sports, entertainment, and recreation activities. Note that the high-tech and low-tech subdivision is not defined for mining and quarrying activities, utilities, and constructions.

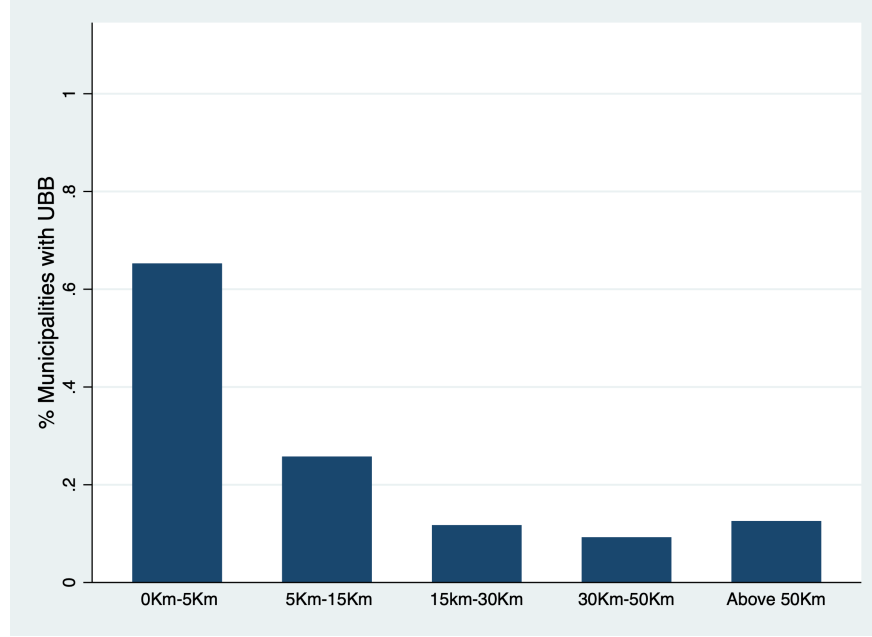
Table 3: Sample summary statistics: employment

Variable	Mean or %	Std. dev.	25th ptc.	Median	75th ptc.
Employees	66.298	676.601	15	22	43
Blue-collar workers	33.049	288.443	6	12	24
White-collar workers	27.109	478.944	2	7	16
Middle managers	3.081	92.249	0	0	0
Top managers	0.837	9.380	0	0	0
Under-29 workers	10.302	152.372	1	3	7
Workers aged 30-49	37.984	309.316	8	13	25
Over-50 workers	18.012	294.311	3	6	12
Share of blue-collar workers	0.565	0.327	0.313	0.656	0.833
Share of white-collar workers	0.358	0.304	0.111	0.263	0.565
Share of middle managers	0.019	0.061	0	0	0
Share of top managers	0.008	0.029	0	0	0
Share of under-29 workers	0.165	0.150	0.059	0.125	0.235
Share of workers aged 30-49	0.580	0.150	0.485	0.583	0.683
Share of over-50 workers	0.255	0.159	0.135	0.241	0.357
High-wage blue-collar workers	8.815	77.063	0	2	7
Low-wage blue-collar workers	7.989	68.097	0	2	6
High-wage white-collar workers	7.166	120.997	0	1	5
Low-wage white-collar workers	6.851	119.770	0	1	4
High-wage middle managers	0.840	22.907	0	0	0
Low-wage middle managers	0.826	23.437	0	0	0
High-wage top managers	0.265	2.756	0	0	0
Low-wage top managers	0.278	2.771	0	0	0
Share of high-wage blue-collar workers	0.154	0.171	0	0.100	0.235
Share of low-wage blue-collar workers	0.135	0.171	0	0.072	0.200
Share of high-wage white-collar workers	0.097	0.127	0	0.059	0.143
Share of low-wage white-collar workers	0.092	0.119	0	0.059	0.133
Share of high-wage middle managers	0.006	0.024	0	0	0
Share of low-wage middle managers	0.006	0.023	0	0	0
Share of high-wage top managers	0.003	0.013	0	0	0
Share of low-wage top managers	0.003	0.013	0	0	0
Observations: 747,184					

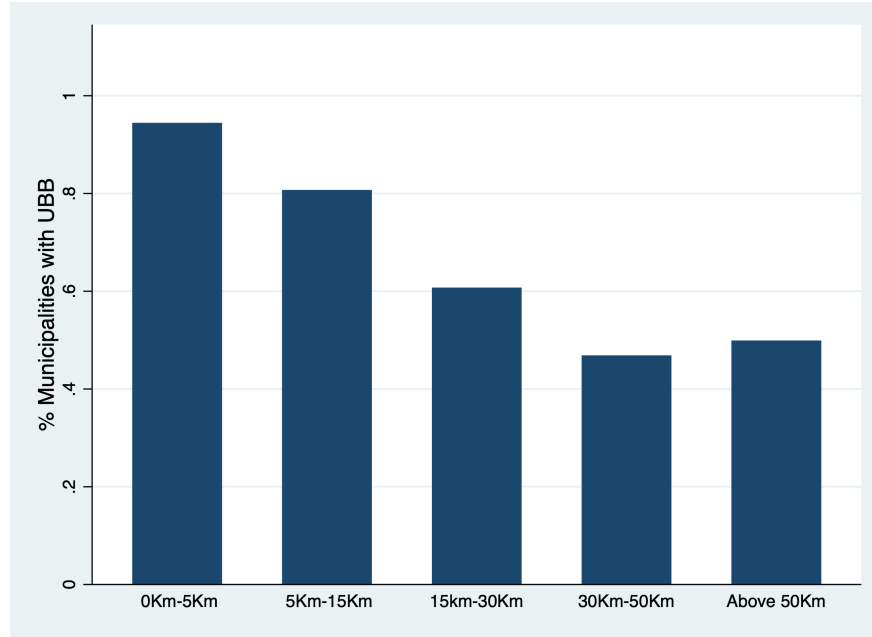
Source: UBB-INPS data set (2012-2019).

“High-wage workers” and “Low-wage workers” are identified with respect to a reference cell. We computed the distribution of contractual daily wages for each year, province, sector (ATECO 2007, 2-digit level), firm size (i.e., small, medium-sized, and large firms), job contract (e.g., blue-collar workers, white-collar workers, etc.), age class (i.e., under-29 workers, workers aged 30-49, and over-50 workers), temporary *versus* open-end status, and part-time *versus* full-time status. For each worker, we have then attached the label “high-wage” if his/her daily wage was equal or above the 75th percentile of the corresponding daily wage distribution defined at the cell level. On the contrary, we have defined a worker to be “low-wage” if his/her daily wage was equal or below the 25th percentile of the corresponding cell. Finally, for each firm and year, we computed the number of high-wage and low-wage workers for each job position (e.g., the number of high-wage blue-collar workers, the number of low-wage blue-collar workers, etc.). The shares of the various categories of workers are defined with respect to the total number of employees in the firm (e.g., the share of blue-collar workers is defined as the number of blue-collar workers over the total number of employees in the firm).

Figure 2: UBB diffusion by different OPB_m levels



(a) 2015

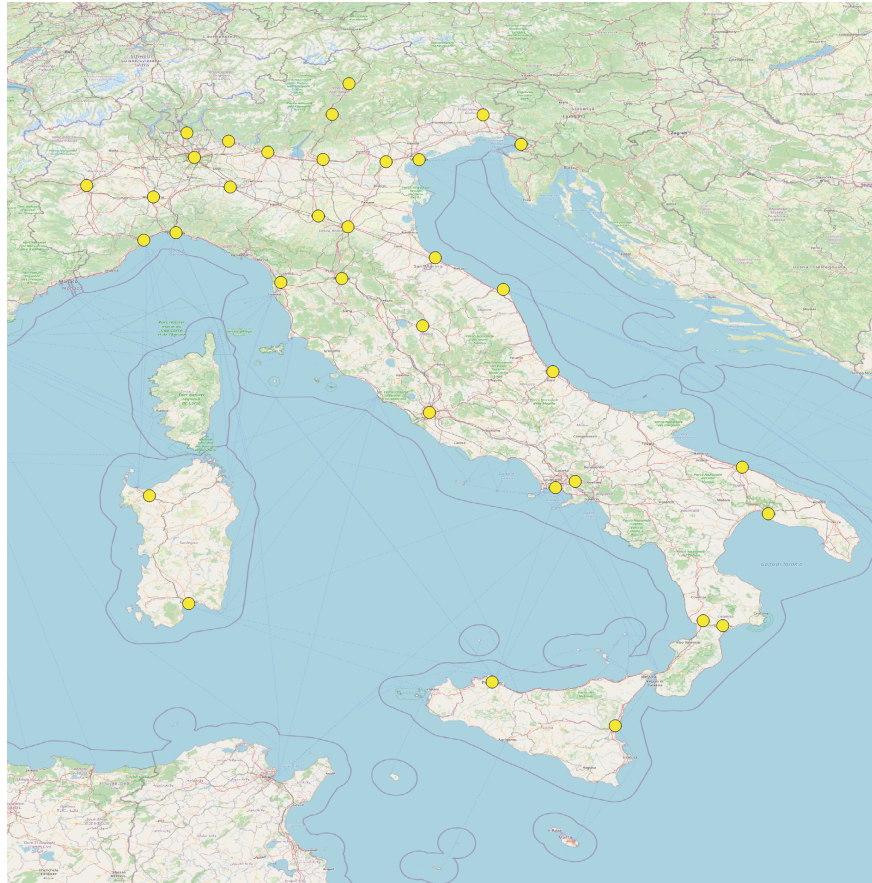


(b) 2019

Source: UBB data set (2012-2019).

The figure shows the percentage of municipalities with access to UBB for different classes of OPB_m . Table 1 reports the list of broadband acronyms and variables, with related descriptions.

Figure 3: **Location of the OPB nodes**



Source: UBB data set.

Table 1 reports the list of broadband acronyms and variables, with related descriptions.

Table 4: **The impact of UBB on overall employment**

	Dep. var.: $\log(\text{employees}_{i,m,t})$			
	OLS1 (1)	OLS2 (2)	OLS3 (3)	IV1 (4)
$UBB_{m,t}$	+0.002 (0.001)	+0.001 (0.001)	−0.0004 (0.001)	+0.027** (0.013)
Cov. 1 $\times$ year dummies	-	yes	yes	yes
Cov. 2 $\times$ year dummies	-	-	yes	yes
Firm age dummy	yes	yes	yes	yes
Size dummies	yes	yes	yes	yes
Sector dummies	yes	yes	yes	yes
Year-region dummies	yes	yes	yes	yes
Municipality fixed effects	yes	yes	yes	-
Firm fixed effects	yes	yes	yes	yes
First-stage F-test	-	-	-	84.35
Observations	747,184	747,184	747,184	747,184

Source: UBB-INPS data set (2012-2019).

The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. Table 1 reports the list of broadband acronyms and variables, with related descriptions. “Cov. 1” includes the following basic municipality-level controls: (i) population, (ii) nominal GDP, and (iii) total area (5 classes). Both (i) and (ii) refer to the baseline year 2012, whereas (iii) is obtained from the 2011 Italian Census. “Cov. 2” comprises the following municipality-level controls pertaining to the average workforce composition of the firms within the municipality: (i) the average firm-level shares of blue-collar workers, white-collar workers, and managers (including both middle and top managers) in the municipality, (ii) the average firm-level shares of under-29 workers, workers aged between 30 and 49, and over-50 workers in the municipality, (iii) the average firm-level shares of temporary workers in the municipality. (i), (ii), and (iii) are computed at the baseline year 2012. “Firm age dummy” is a dummy variable which is equal to 1 if the firm age is above 10 years and 0 otherwise. Sector is defined at the ATECO 2007, 3-digit level. “Year-region dummies” includes dummies for the interactions between Italy’s 20 administrative regions and year.

Table 5: **First-stage regression**

	Dep. var.: $UBB_{m,t}$
$Post_{2015} \times OPB_m$	-0.003^{***} (0.0004)
Cov. 1 $\times$ year dummies	yes
Cov. 2 $\times$ year dummies	yes
Firm age dummy	yes
Size dummies	yes
Sector dummies	yes
Year-region dummies	yes
Firm fixed effects	yes
First-stage F-test	84.35
Observations	747,184

Source: UBB-INPS data set (2012-2019).

The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. The table reports the first-stage regression of the IV regression in Column (4) of Table 4. Table 1 reports the list of broadband acronyms and variables, with related descriptions. For other information, related to the description of controls, see the footnote to Table 4.

Table 6: **The impact of UBB on different types of employment by job position and workers' age**

<i>Job position</i>	
Dep. var.: Blue-collar workers (log)	
$UBB_{m,t}$	-0.018 (0.017)
Dep. var.: White-collar workers (log)	
$UBB_{m,t}$	+0.024 (0.018)
Dep. var.: Middle managers (log)	
$UBB_{m,t}$	+0.052*** (0.014)
Dep. var.: Top managers (log)	
$UBB_{m,t}$	-0.001 (0.007)
<i>Workers' age</i>	
Dep. var.: Under-29 workers (log)	
$UBB_{m,t}$	-0.030 (0.026)
Dep. var.: Workers aged 30-49 (log)	
$UBB_{m,t}$	+0.004 (0.017)
Dep. var.: Over-50 workers (log)	
$UBB_{m,t}$	+0.099*** (0.023)
First-stage F-test	84.35
Observations	747,184

Source: UBB-INPS data set (2012-2019).

IV estimates. The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. This table replicates the IV estimation in Column (4) of Table 4, for each of the considered dependent variables. Such dependent variables collect the quantities of the considered workers' categories (in logarithm) employed in firm i , operating in municipality m , in year t . For example, the first dependent variable considered (i.e., first panel of the table) is the number of blue-collar workers employed in firm i at time t , the second variable is the number of white-collar workers, and so on. Table 1 reports the list of broadband acronyms and variables, with related descriptions. For other information, related to the description of controls, see the footnote to Table 4.

Table 7: The impact of UBB on different types of employment by job position and workers' age in high-tech *versus* low-tech firms

	High-tech (1)	Low-tech (2)
<i>Job position</i>		
Dep. var.: Blue-collar workers (log)		
$UBB_{m,t}$	−0.031 (0.052)	−0.033* (0.017)
Dep. var.: White-collar workers (log)		
$UBB_{m,t}$	+0.031 (0.041)	+0.028 (0.021)
Dep. var.: Middle managers (log)		
$UBB_{m,t}$	+0.110*** (0.038)	+0.034** (0.014)
Dep. var.: Top managers (log)		
$UBB_{m,t}$	+0.020 (0.021)	+0.006 (0.007)
<i>Workers' age</i>		
Dep. var.: Under-29 workers (log)		
$UBB_{m,t}$	−0.091 (0.065)	−0.034 (0.029)
Dep. var.: Workers aged 30-49 (log)		
$UBB_{m,t}$	+0.019 (0.036)	−0.013 (0.019)
Dep. var.: Over-50 workers (log)		
$UBB_{m,t}$	+0.122*** (0.045)	+0.082*** (0.025)
First-stage F-test	61.52	88.25
Observations	173,280	521,592

Source: UBB-INPS data set (2012-2019).

IV estimates. The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. This table replicates Table 6, but runs separate regressions for high-tech and low-tech firms. High-tech and low-tech sectors are defined as in Table 2. Table 1 reports the list of broadband acronyms and variables, with related descriptions. For other information, related to the description of controls, see the footnote to Table 4.

Table 8: **The impact of UBB on different types of employment by skill level in high-tech *versus* low-tech firms**

	High-tech (1)	Low-tech (2)
<i>Skill level by job position</i>		
Dep. var.: High-wage blue-collar workers (log)		
$UBB_{m,t}$	−0.043 (0.052)	−0.050* (0.027)
Dep. var.: Low-wage blue-collar workers (log)		
$UBB_{m,t}$	−0.047 (0.054)	+0.021 (0.030)
Dep. var.: High-wage white-collar workers (log)		
$UBB_{m,t}$	+0.111** (0.052)	+0.047** (0.021)
Dep. var.: Low-wage white-collar workers (log)		
$UBB_{m,t}$	+0.041 (0.055)	−0.013 (0.023)
Dep. var.: High-wage middle managers (log)		
$UBB_{m,t}$	+0.044* (0.025)	+0.002 (0.009)
Dep. var.: Low-wage middle managers (log)		
$UBB_{m,t}$	+0.047 (0.029)	+0.020** (0.009)
Dep. var.: High-wage top managers (log)		
$UBB_{m,t}$	+0.021 (0.017)	−0.004 (0.006)
Dep. var.: Low-wage top managers (log)		
$UBB_{m,t}$	+0.022 (0.020)	−0.002 (0.006)
First-stage F-test	61.52	88.25
Observations	173,280	521,592

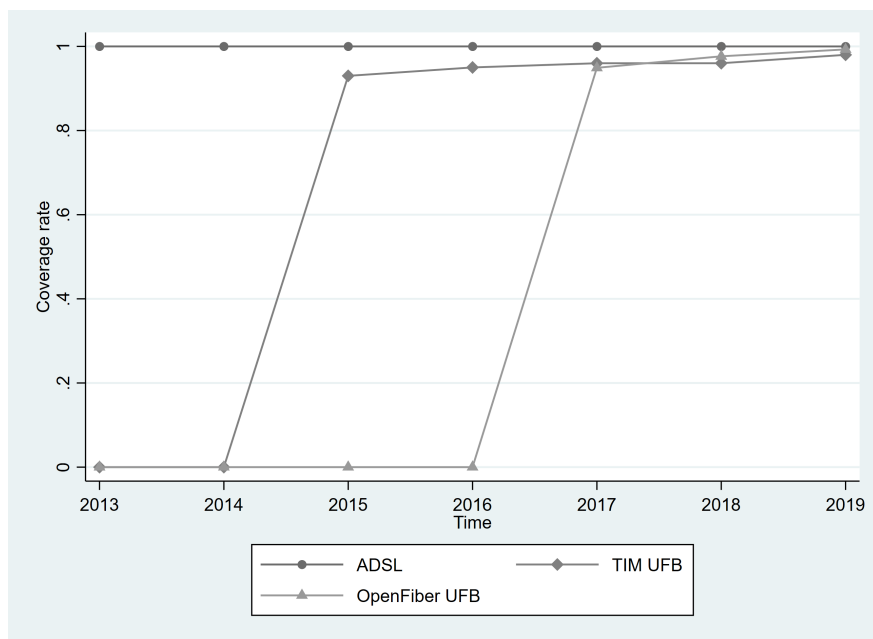
Source: UBB-INPS data set (2012-2019).

IV estimates. The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. This table replicates Table 7, but focuses on skill level, computed based on relative wages, as defined in Table 3. High-tech and low-tech sectors are defined as in Table 2. Table 1 reports the list of broadband acronyms and variables, with related descriptions. For other information, related to the description of controls, see the footnote to Table 4.

Appendices

A. Additional broadband-related information

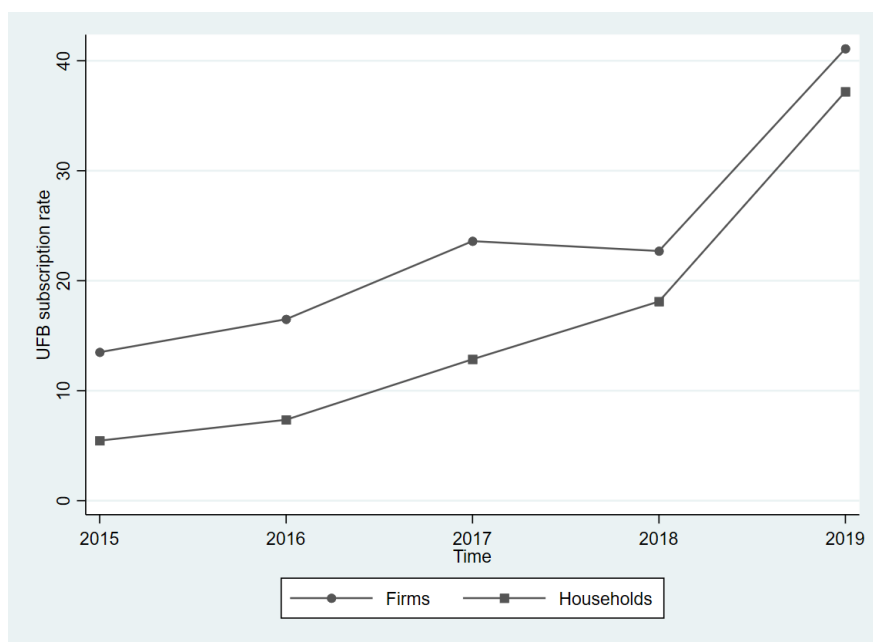
Figure A.1: **Within-municipality UFB variation**



Source: UBB data set (2012-2019).

The coverage rate indicates the percentage of households that have access to the specified broadband technologies. The figure reports data for a large Italian municipality. Table 1 reports the list of broadband acronyms and variables, with related descriptions.

Figure A.2: UFB adoption



Source: European Council and ISTAT.

The UFB subscription rate indicates the percentage of households that subscribed to a UFB connection service. Table 1 reports the list of broadband acronyms and variables, with related descriptions.