
INPS

Istituto Nazionale Previdenza Sociale

agosto 2026 – numero 123

WorkINPS *Papers*

# Advanced Digital Technologies and Firm Workforce Composition

# Tecnologie digitali avanzate e composizione della forza lavoro nelle imprese

Laura Abrardi
Carlo Cambini
Elena Grinza
Lorien Sabatino

ISSN 2532 -8565

Lo scopo della serie WorkINPS papers è quello di promuovere la circolazione di documenti di lavoro prodotti da INPS o presentati da esperti indipendenti nel corso di seminari INPS, con l'obiettivo di stimolare commenti e suggerimenti.
Le opinioni espresse negli articoli sono quelle degli autori e non coinvolgono la responsabilità di INPS.

The purpose of the WorkINPS papers series is to promote the circulation of working papers prepared within INPS or presented in INPS seminars by outside experts with the aim of stimulating comments and suggestions.
The views expressed in the articles are those of the authors and do not involve the responsibility of INPS.



*In copertina: uno storico "Punto cliente" a Tuscania*
*INPS, Direzione generale, Archivio storico*

## I WORKINPS PAPER

Le basi dati amministrative dell'*INPS* rappresentano una fonte statistica unica per studiare scientificamente temi cruciali per l'economia italiana, la società e la politica economica: non solo il mercato del lavoro e i sistemi di protezione sociale, ma anche i nodi strutturali che impediscono all'Italia di crescere in modo adeguato. All'interno dell'Istituto, questi temi vengono studiati sia dai funzionari impiegati in attività di ricerca, sia dai *VisitInps Scholars*, ricercatori italiani e stranieri selezionati in base al loro curriculum vitae e al progetto di ricerca presentato.

I **WORKINPS** hanno lo scopo di diffondere i risultati delle ricerche svolte all'interno dell'Istituto a un più ampio numero possibile di ricercatori, studenti e policy markers.

Questi saggi di ricerca rappresentano un prodotto di avanzamento intermedio rispetto alla pubblicazione scientifica finale, un processo che nelle scienze sociali può chiedere anche diversi anni. Il processo di pubblicazione scientifica finale sarà gestito dai singoli autori.

**Agar Brugiavini**

# Advanced Digital Technologies and Firm Workforce Composition

# Tecnologie digitali avanzate e composizione della forza lavoro nelle imprese

**Laura Abrardi**
(Associate Professor of Applied Economics)
(POLITO)

**Carlo Cambini**
(Full Professor of Applied Economics)
(POLITO)

**Elena Grinza**
(Associate Professor of Economic Policy)
(UNITO)

**Lorien Sabatino**
(Assistant Professor of AppliedEconomics)
(POLITO)

# Advanced Digital Technologies and Firm Workforce Composition

# Tecnologie digitali avanzate e composizione della forza lavoro nelle imprese

Laura Abrardi[a], Carlo Cambini[a], Elena Grinza[b,*], Lorien Sabatino[a]

[a]*Department of Management Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24 - 10129, Turin (Italy)*
[b]*Department of Economics, Social Studies, Applied Mathematics, and Statistics, University of Turin, Corso Unione Sovietica 218/bis - 10134, Turin (Italy); Collegio Carlo Alberto; CEBRIG - Université Libre de Bruxelles; LABORatorio Riccardo Revelli*

**Abstract**

This paper examines the impact of last-generation digital technologies on firms' labor demand by leveraging the phased rollout of ultra-fast broadband (UBB) connections in Italy. We combine municipality-level data on UBB deployment with rich administrative employer–employee records to build a balanced panel of firms active between 2012 and 2019. To address potential endogeneity, we employ an instrumental variable strategy exploiting plausibly exogenous variation in the distance between each firm's location and the nearest backbone node of the telecommunications infrastructure. Our estimates indicate that UBB availability leads to an overall increase in firm-level employment. Disaggregating by worker type, we find strong complementarities between UBB and high-skill jobs, particularly in high-tech sectors, while in low-tech firms, we find evidence of displacement among high-wage blue-collar workers, consistent with a decline in specialized manual jobs. These results highlight heterogeneous employment effects across industries and occupations, suggesting that broadband infrastructure could exacerbate labor market inequalities in the absence of complementary policies.

Questo articolo esamina l'impatto delle tecnologie digitali di ultima generazione sulla domanda di lavoro delle imprese, sfruttando l'introduzione graduale delle connessioni a banda

*Laura Abrardi, Associate Professor of Applied Economics (POLITO), laura.abrardi@polito.it; Carlo Cambini, Full Professor of Applied Economics (POLITO), carlo.cambini@polito.it; Elena Grinza, Associate Professor of Economic Policy (UNITO), elena.grinza@unito.it; Lorien Sabatino, Assistant Professor of Applied Economics (POLITO), lorien.sabatino@polito.it. This paper was made possible thanks to sponsorships and liberal donations in support of the "VisitINPS Scholars" programme. We kindly acknowledge the data access provided by the VisitINPS program. The findings and conclusions expressed are solely those of the authors and do not represent the views of INPS. We would like to thank Edoardo Di Porto for his general help with INPS data usage. We are also grateful to Mario Mirabelli (TIM-LAB) and Francesco Nonno (OpenFiber) for providing us with access to and guidance on the broadband data used in this paper. We acknowledge financial support from TIM-LAB (Turin). The views expressed herein represent those of the authors and do not reflect in any case the opinions of the companies and institutions that provided the data and funding.

ultra-larga in Italia. Combiniamo dati a livello comunale sulla diffusione della banda ultra-larga con ricchi archivi amministrativi employer–employee per costruire un panel bilanciato di imprese attive tra il 2012 e il 2019. Per affrontare potenziali problemi di endogeneità, adottiamo una strategia a variabili strumentali che sfrutta la variazione plausibilmente esogena nella distanza tra la sede di ciascuna impresa e il nodo backbone più vicino dell'infrastruttura di telecomunicazioni. Le nostre stime indicano che la disponibilità della banda ultra-larga determina un aumento complessivo dell'occupazione a livello di impresa. Disaggregando per tipologia di lavoratore, riscontriamo forti complementarietà tra banda ultra-larga e occupazioni ad alta qualificazione, in particolare nei settori ad alta tecnologia; nelle imprese a bassa tecnologia, invece, troviamo evidenza di spiazzamento tra gli operai ad alta retribuzione, coerentemente con un declino delle mansioni manuali specializzate. Questi risultati evidenziano effetti occupazionali eterogenei tra settori e professioni, suggerendo che le infrastrutture a banda larga potrebbero accentuare le disuguaglianze nel mercato del lavoro in assenza di politiche complementari.

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

*Parole chiave:* Banda ultra-larga, reti in fibra ottica, occupazione a livello di impresa, capitale umano, dati integrati employer–employee.

*JEL:* L96, M51, J24.

## 1. Introduction

New business models are emerging in the App Economy and the Internet of Things, driven by evolving needs for storage, processing, and software capabilities, including cloud computing, data analytics, and artificial intelligence. These technological advances are reshaping business processes and organizational structures, with potentially significant implications for firms' workforce composition, depending on the extent to which workers are complements or substitutes for new information technologies.

In this paper, we examine the Italian case to assess how last-generation digital technologies (DT) influence firms' labor demand, exploiting the staggered rollout of ultra-fast broadband (UBB) connections across municipalities.[1] Beginning in 2015, substantial investments, primarily from the national incumbent telecommunications operator, were directed

[1] In June 2023, the US announced its largest-ever investment in high-speed internet to achieve universal coverage by 2030. In Europe, the Commission reaffirmed its goal of transforming the continent into a Gigabit Society by 2025, ensuring high-speed access for all households. Similar national broadband plans have been adopted in countries such as Australia, Japan, Mexico, and several African nations.

toward UBB deployment.[2] Fiber-based UBB delivers markedly higher performance than traditional copper-wire (ADSL) broadband in terms of bandwidth, security, speed, reliability, signal strength, and cloud access.[3] Faster connections enable more users to perform online tasks simultaneously and efficiently within an organization, improving overall productivity. High-speed connectivity also underpins business management applications such as Enterprise Resource Planning (ERP) systems, which store, retrieve, and share production and sales data in real time via cloud computing, feasible only with UBB. In short, amid the broader shift toward online application software, UBB represents a key enabling technology for accessing business digital services (Cambini and Sabatino, 2023; DeStefano et al., 2023; Nicoletti et al., 2020, among others).

Ex ante, firms may respond differently to shocks from DT. Previous evidence indicates that traditional DT reduced the labor share of GDP (Autor et al., 2020) and generated labor market dynamics favoring a minority of workers, leading firms to substantially reallocate their workforce toward skilled labor (Akerman et al., 2015). However, advanced DT can also substitute for tasks previously performed by highly skilled workers (Webb, 2019). Conversely, complementarities with tacit knowledge, typically embodied in managers and experienced employees, may instead benefit relatively older workers (Barth et al., 2023).

We study these trade-offs by examining the relationship between UBB availability and firm-level workforce dynamics, focusing on the intensive margin of employment. Specifically, we analyze both the overall size of firms' workforces and their composition, conditional on firm and location characteristics. Our analysis draws on uniquely rich administrative matched employer–employee data from the Italian Social Security System (INPS), covering the entire population of private-sector firms in Italy with at least 10 employees over 2012–2019. The balanced panel comprises 747,184 firm-year observations. For each firm and year, we identify all employees and observe several characteristics, including contract type, age, and wage, from which we derive their skill level.

Using firm-level data is essential in our context for two main reasons. First, it allows us to identify the microeconomic channels through which UBB availability affects employment within firms, an analysis that would be impossible with more aggregated data (Nucci and Pozzolo, 2010). Second, it enables us to capture heterogeneous effects, as firms vary in size, sector, location, digital intensity, and pre-existing ICT adoption, all of which can shape their

[2] Due to EU State aid regulations (TFEU, art. 107), the Italian government did not finance UBB deployment nationwide. Instead, it targeted public funds to specific areas, particularly rural and sparsely populated municipalities where private investment was unprofitable. A new market entrant, OpenFiber, launched in 2017, further accelerating deployment.

[3] See TIM Netbook, 2018, available at `https://rete.gruppotim.it/sites/default/files/download/TIMNetbook-FY2018-web_0.pdf`.

response to DT shocks.

Our empirical strategy exploits the staggered rollout of UBB across Italian municipalities where firms operate. Because deployment relied primarily on private investment, estimating the impact of UBB is challenging due to potential unobserved, time-varying economic factors correlated with both UBB investment decisions and microeconomic outcomes (Cambini et al., 2023; Campante et al., 2017; Falck et al., 2014; Gavazza et al., 2018). To address this concern and identify causal effects, we adopt an instrumental variable (IV) approach that leverages plausibly exogenous variation in the distance between a firm's municipality and the nearest national optical packet backbone (OPB) node (hereafter, "OPB node" or simply "node"; Cambini and Sabatino, 2023; Campante et al., 2017; Miner, 2015). These nodes are upgraded facilities of the legacy telephone network built in the early 2000s; their locations are plausibly exogenous to labor outcomes once firm-level fixed effects and common time trends are controlled for. We validate the instrument through reduced-form estimates showing no pre-UBB correlation between distance to the closest node and firm-level employment. The inclusion of firm fixed effects ensures that identification relies on within-firm variation over time, comparing outcomes before and after UBB rollout in treated municipalities to those in municipalities where UBB has not yet been introduced, while addressing endogeneity through the IV framework.

Our results indicate that firm-level employment increases by 2.7% following the UBB rollout, suggesting that firms demand more workers as a result of advanced DT. Disaggregating by job contract type and worker age, we find that this effect is driven by growth in middle management and in workers over 50, pointing to complementarities with experienced, high-level positions. The pattern is stronger in high-tech firms, where the number of middle managers rises by an estimated 11% after UBB introduction, but it is also present in low-tech firms (+3.4%). We further classify workers by relative wage level, used as a proxy for skills, identifying high- and low-wage employees within each firm and contract type, based on their wage relative to a narrowly defined reference cell. In high-tech firms, UBB shows strong complementarities with high-level positions, both in managerial roles (high-wage middle managers) and in highly specialized white-collar jobs (high-wage white-collar workers). In low-tech firms, these complementarities are present but more modest. Finally, while no substitution effects emerge in high-tech sectors, we find evidence in low-tech firms of displacement among high-wage blue-collar workers, consistent with a decline in specialized manual jobs.

All in all, our findings suggest that advanced DT can increase firms' demand of managerial positions, particularly in sectors requiring higher digital skills, such as high-tech industries. This is consistent with the existence of a substantial skill-based digital divide

(Akerman et al., 2015; Card and DiNardo, 2002; Goos et al., 2014; OECD, 2018), whereby firms reconfigure their workforce in favor of employees best able to exploit the opportunities of the digital revolution. Recent evidence indicates that higher ICT skills raise the abstract task content of jobs while reducing their routine and manual components (Gaggl and Wright, 2017). Our results also align with the literature on ICT-induced labor market polarization (e.g., Autor et al., 2003), which shows that DT tend to replace workers in routine tasks, whether cognitive or manual, that follow explicit rules and are therefore more susceptible to automation. Such tasks (e.g., bookkeeping, process monitoring, information processing) are typically concentrated in the middle of the wage distribution. By contrast, advanced information technologies complement workers in non-routine tasks involving problem-solving, decision-making, and complex communication (Falck et al., 2021).[4] Non-routine tasks are associated either with conceptual jobs at the top of the wage distribution (e.g., managerial and professional positions) or with certain manual jobs at the bottom.

Most available studies on broadband technologies' labor market effects focus on basic broadband (i.e., ADSL connections), finding positive impacts on wages and employment but only for specific worker groups or regions (Forman et al., 2012; Akerman et al., 2015; Czernich et al., 2011). This literature highlights complementarities between basic broadband and workers' skills (Akerman et al., 2015), with effects typically concentrated in high-income areas and IT-intensive sectors (Forman et al., 2012). Focusing specifically on high-speed broadband, recent evidence shows a positive impact of UBB on self-employment (Abrardi et al., 2024), indicating important complementarities with organizational capital investments (Fabling and Grimes, 2021). Overall, these findings suggest that UBB contributes to expanding high-income cognitive jobs, consistent with the task-based approach to skill-biased technological change (Autor et al., 2003). Moreover, high-speed broadband availability appears linked to firm growth. Technologies like cloud computing have shifted IT costs to largely variable, on-demand subscriptions, enabling firms to scale operations rapidly without quasi-irreversible hardware investments, benefiting especially small firms (DeStefano et al., 2023).

Our contribution to the literature is threefold. First, we provide novel causal evidence on how the introduction of UBB, a key enabling infrastructure for advanced digital applications and managerial practices, affects firms' workforce composition in terms of job roles, age, and skill levels. Unlike most existing studies that rely on aggregate or sector-level data, we exploit a rich matched employer-employee panel of private-sector firms, enabling us to capture detailed heterogeneity in firm-level labor adjustments. Second, we are among the first to

[4]For instance, computer-based teaching methods and virtual learning technologies have been found to complement traditional teaching and enhance students' ability to search for ideas and information (Falck et al., 2018).

analyze how UBB's effects vary by firms' technological intensity, showing that digital infrastructure complements high-skilled labor more strongly in high-tech sectors while potentially displacing specialized manual jobs in low-tech firms. Third, we employ a robust instrumental variable strategy exploiting historical infrastructure, namely, proximity to national optical backbone nodes, which allows us to isolate plausibly exogenous variation in UBB availability and address endogeneity concerns that commonly challenge empirical broadband studies.

From a policy perspective, our results highlight the critical importance of aligning digital infrastructure investments with policies that foster digital skills development and workforce adaptability. The heterogeneous employment effects we observe suggest that, without complementary human capital policies, digitalization risks exacerbating existing skill-based labor market inequalities.

The remainder of the paper is organized as follows. Section 2 provides an overview of the UBB infrastructure rollout in Italy and introduces the data. Section 3 describes the empirical model and identification strategy. Section 4 presents the main findings on the impact of UBB on overall firm-level employment. Section 5 investigates heterogeneity in UBB's effects across job contract types, worker age and skills, and firms' technological intensity. Finally, Section 6 concludes and discusses the policy implications of our results.

## 2. Data

### *2.1. Matched employer-employee data*

We utilize a uniquely rich annual administrative matched employer-employee dataset covering the entire population of private-sector Italian firms, provided by INPS. Our empirical analysis focuses on a balanced panel of firms with at least 10 employees (i.e., excluding micro firms) over the period 2012–2019. The INPS data include detailed information on workers', jobs', and firms' characteristics. This dataset comprises three main components. The first is the "worker archive," which contains personal data about workers (e.g., age). The second is the "job archive," recording yearly gross earnings, days worked during the calendar year, job contract type (e.g., blue-collar worker, white-collar worker, middle manager, top manager), and contract duration (fixed-term versus open-ended). Finally, the "firm archive" provides firm-level information, including location, establishment date, and sector of activity.[5]

[5]It is important to clarify that our data are at the firm level, not at the establishment level. Firms in the INPS data are uniquely identified by the variable `id_impresa`, corresponding to the fiscal code, which does not distinguish between different production units. Although the INPS archives also include `id_azienda` (the social security contribution number), this identifier does not uniquely capture establishment-level information either. In fact, no variable in the INPS administrative data reliably identifies individual establishments. While multi-establishment firms could theoretically operate in multiple municipalities with varying exposure

Starting from the worker-level data, for each firm and year, we calculate the total number of employees. This variable serves as our main dependent variable to empirically investigate whether, and how, UBB connections affect a firm's employment level. As detailed below, we use the natural logarithm of the number of employees, denoted as $log(employees_{i,m,t})$, where $i$ indexes the firm, $m$ the municipality where the firm is located, and $t$ the year.[6]

We then calculate various workforce characteristics for each firm and year, which serve as additional dependent variables. These include the number of workers by age group as well as by job contract type. For the age categories, we compute the numbers of workers under 30, between 30 and 49, and 50 years and older. Regarding job contracts, we calculate the numbers of blue-collar workers, white-collar workers, middle managers, and top managers. All these variables are included in the empirical analysis (in logarithms) to investigate the impact of UBB on employment across different age and job contract groups within 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 their daily wage is equal to or above the 75th percentile of the corresponding daily wage distribution defined at the cell level. Conversely, we define a worker to be "low-wage" if their 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 compared with the wages of the blue-collar workers in the reference cell, that is, working within the same sector and location,

to UBB rollout, Belotti et al. (2021) show that the vast majority of Italian firms are single-establishment entities, minimizing this concern. This finding aligns with an industrial structure dominated by small and medium-sized enterprises. Consistent with official statistics, only 3.2% of firms in our sample are large and thus more likely to have multiple establishments. As a robustness check, we exclude large firms and find that our results remain virtually unchanged (available upon request).

[6]The logarithmic transformation is also applied to all other dependent variables in the paper, which represent the firm-level number of employees by job contract type, age group, and skill level. Since the key regressor, $UBBm,t$, is a binary variable, the estimated coefficients should be interpreted as semi-elasticities.

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.[7]

*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 rollout conducted by this operator since the introduction of UBB in Italy in 2015. The second data source comes from OpenFiber, the only alternative UBB operator, which entered the market in 2017, and provides additional information on the municipalities covered by OpenFiber. 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 began in 2015 following the implementation of the Italian Strategy for High-Speed Broadband, aligned with the primary objectives of the 2020 Digital Agenda for Europe.[8] The UBB deployment plan has been carried out through a mix of public and private investments. As noted earlier, only two distinct networks provide UBB services to end consumers. The first belongs to the incumbent telecom operator TIM, which utilizes pre-existing telecommunications infrastructure originally designed for voice telephony and ADSL connections. Accordingly, TIM has been the first to invest in UBB infrastructure across Italy since 2015, covering the vast majority of municipalities with a combination of full-fiber (FTTH) and copper-fiber (FTTC) connections. The second network is operated by OpenFiber, a wholesale provider currently owned by Cassa Depositi e Prestiti, the investment arm of the Italian Ministry of Treasury, alongside two international private investment funds. OpenFiber entered the market in 2017 by acquiring Metroweb, a

[7]Note that we can precisely measure a worker's contractual daily wage in each year, by dividing their yearly gross earnings by 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".

[8]The Digital Agenda for Europe specifies network coverage and service adoption goals for the entire European population. See `https://www.europarl.europa.eu/factsheets/en/sheet/64/digital-agenda-for-europe` for more information.

private telecom company with coverage in several large cities such as Milan and Turin. Since then, OpenFiber has focused investments on FTTH connections primarily in large urban centers as well as in less densely populated "white areas", having received public funding through competitive tenders organized by the Italian Government. By the end of 2019, OpenFiber had covered 392 out of approximately 8,000 Italian municipalities, 261 of which were also fully or partially covered by TIM.[9] Figure 1 illustrates the spread of UBB in Italy. As shown, by the end of 2019, around 55% of Italian municipalities offered UBB services with speeds exceeding 30 Mbps, serving about 90% of the population. In contrast, ADSL connections have reached maturity, with nearly universal availability across municipalities and populations.

Our primary regressor of interest, $UBB_{m,t}$, is a binary indicator variable that takes the value one if municipality $m$ has access to UBB connections in year $t$, and zero otherwise.[10] It is important to note that our UBB indicator specifically refers to the presence of these connections within a municipality during the relevant year. One notable concern regarding this indicator is whether the deployment 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 valid proxy for the availability of UBB connections to businesses.

Furthermore, we have access to detailed information on the incumbent's telecommunication infrastructure, which includes components operating at both national and local levels. At the national level, data transmission flows through the backbone network, where multiple nodes are interconnected via optical fiber connections. At the local level, traffic is then routed to the local central offices, from which the "last mile" connection originates, linking the service provider to end-users. It is important to note that both the nodes and local central offices are pre-existing facilities from the legacy telephone network, established well before the introduction of UBB.[11] Using this information, we construct a key component of our instrumental variable, $OPB_m$, which measures the distance (in kilometers) between each municipality and its closest node (see the discussion in Section 3).

[9]OpenFiber's deployment plan is available at `https://openfiber.it/area-infratel/piano-copertura/`.

[10]This 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 jump in the UBB coverage rate within municipalities, with a sharp increase to nearly one when UBB is introduced in the municipality.

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

Finally, we obtain municipality-level data from the Italian National Institute of Statistics (ISTAT). These variables, included as controls in the regressions, comprise, among others, the current population of municipality $m$ in year $t$ and the total area of the municipality (the latter derived from the 2011 Italian Census).

We merge firm-level INPS data with municipality-level UBB (and ISTAT) data using the firms' municipality identifiers provided by INPS. Specifically, we determine whether each firm is located in a municipality with UBB connectivity at each time point. Our final merged dataset includes 747,184 firm-year observations, covering a total of 93,398 firms.

### *2.3. Descriptive statistics*

Table 2 provides a comprehensive summary of our final dataset. The average firm size is relatively modest, with approximately 66 employees, reflecting the dominance of small and medium-sized enterprises in the Italian industrial landscape. The median firm size is 22 employees, indicating that half of the firms in the sample are classified as small. We observe that 49.7% of firm-year observations have UBB coverage. Restricting the sample to years following the UBB rollout, this share increases to 79.6%. Firms in our dataset have an average age of approximately 22 years. Regarding sectoral distribution, 37.5% of firms operate in manufacturing, 5.5% in construction, 17.4% in trade, and 38% in services. A smaller fraction operates in mining, quarrying, or utilities sectors. Geographically, about one-third of firms are located in North-West Italy (34.6%), 28.4% in the North-East, 17.9% in the Center, and 19.1% in the South and Islands. In terms of technological intensity, 24.9% of firms are classified as high-tech, while the remaining 75.1% are low-tech.[12]

[12] 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. 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

Table 3 offers a detailed breakdown of the workforce composition within the firms analyzed. Specifically, it presents descriptive statistics on the number and share of workers by contract type, including blue-collar workers, white-collar workers, middle managers, and top managers. The workforce is further segmented by age into three groups: young (under 29 years), middle-aged (30 to 49 years), and older workers (50 years and above). Additionally, the table provides information on the number and proportion of workers classified by relative wage levels, distinguishing between "high-wage" and "low-wage" workers as defined in Subsection 2.1. The data reveal that blue-collar workers constitute a substantial share of the average firm's workforce, accounting for 56.5% of employees. White-collar workers also represent a significant portion at 35.8%. Middle and top-level managers collectively make up 2.7% of the workforce. Regarding age distribution, the majority of workers fall within the prime working-age group of 30–49 years, comprising 58% of employees. While unsurprising given the broad age range, this highlights that prime-age workers dominate the workforce. Younger workers (under 29) represent 16.5%, while older workers (50 and above) account for 25.5%.

## 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:

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

The dependent variable is the natural logarithm of the number of workers employed by firm $i$, located in municipality $m$, and year $t$. In all the regressions of the paper, the standard errors are clustered at the municipality level.

Our variable of interest is $UBB_{m,t}$, which identifies municipalities with access to UBB connections. The estimated parameter $\beta$ captures the average effect of UBB availability on the log of firm-level employment, conditional on time-invariant firm characteristics and time-varying municipality characteristics. The design allows for inference on how access to UBB affects the intensive margin of employment within firms (i.e., whether firms expand their workforce). We will also focus on specific job contract types, workers' age, and wage classes to estimate heterogeneous effects across different workers within the firms.

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 construction.

The $X_{m,t}$ vector collects municipality-level controls. It collects baseline municipality characteristics interacted with year dummies, to control very flexibly for heterogeneity in the evolution of firm-level employment based on pre-UBB municipality characteristics.[13] The set of characteristics includes municipality population, aggregate GDP at the municipality level, total area (classified into five groups), and information on the workforce composition of firms located in the municipality. The term $\tau_t$ collects region-year fixed effects, while $\eta_i$ 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 rollout of UBB coincides with the intention-to-treat assignment. The identification of the causal impact of UBB on firm 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 rollout, 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 the geographical location of the incumbent's OPB nodes.[14] 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 rollout 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 (OLT). That is, UBB is first introduced in locations relatively closer to nodes because, in turn, OLT 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

[13] This 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).

[14] Figure 3 depicts the location of the 35 nodes of the incumbent's telecommunication network.

between $OPB_m$ and the OLT diffusion, which, in turn, drives the UBB rollout, thus implying that municipalities relatively closer to nodes are indeed more likely to receive UBB.

Our exclusion restriction assumption is that any correlation between firm employment and the municipality's distance from the closest node is constant around the introduction of UBB and therefore absorbed by the fixed effects. While we employ firm fixed effects, which control for time-invariant differences across firms, including their location, they do not account for potentially different trends between firms located in municipalities closer to or farther from the nodes. In other words, the exclusion restriction could be violated by the presence of underlying municipality-level trends that are correlated with both our instrument and firm employment. For instance, firms located farther from the nodes may exhibit different growth trajectories than those located relatively closer, for reasons unrelated to the UBB rollout. To address this concern, we include time-varying municipality-level controls that flexibly capture differential trends based on baseline municipality characteristics, following a similar empirical strategy as in Cambini and Sabatino (2023) and Campante et al. (2017).

A reduced-form regression of firm employment on $Post_{2015} \times OPB_m$ can be interpreted as a DiD model in which municipalities (and firms) relatively closer to OPB nodes are (more) treated. Hence, we can test the validity of the instrument by checking for parallel trends before the introduction of UBB. To this aim, we estimate the following reduced-form regression:

$$\log(employees)_{i,m,t} = \alpha + \sum_{t} \delta_t OPB_m \times year_t + \theta X_{m,t} + \tau_t + \mu_i + e_{i,m,t}, \tag{2}$$

where $\delta_t$ are the coefficients of interest, that is, those associated with the interactions of $OPB_m$ with year-specific dummies, and the other variables are defined as in Equation (1). If the correlation between $OPB_m$ and firm-level employment is fully driven by the UBB rollout, we should observe no significant correlation before 2015. We thus check whether pre-2015 $\delta_t$s are statistically different from zero. This test, in fact, resembles a standard parallel trend test in a difference-in-differences model, in which the treated units are those firms located relatively closer to the nodes.

Figure 4 depicts the estimated $\delta_t$s with the associated 95% confidence intervals, excluding the 2012 baseline year. The main coefficients of interest are the ones associated with the 2013 and 2014 interaction, which are not statistically different from zero at the 5% level. Hence, $OPB_m$ is not correlated with firm employment before the advent of UBB, thereby validating the exogeneity of the instrument. This experiment is also informative about the expected second-stage results in our two-stage least squares (2SLS) estimation. Since (i) we observe a clear negative relationship between firm employment and $OPB_m$ after 2015 (Figure 4) and (ii) more distant municipalities are less likely to receive UBB connections (Figure 2), our estimates can be expected to yield a positive impact of UBB on firm-level employment.[15]

## 4. The impact of UBB on firm-level 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) includes only 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 (five classes, obtained from the 2011 Italian census). The third OLS regression (OLS3) uses additional municipality-level controls for 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.

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%.

[15] As shown in Angrist and Pischke (2008), the relationship between the dependent variable and the instrument is proportional to the (second-stage) relationship between the dependent variable and the endogenous variable. Hence, reduced-form estimates are informative about the sign of the 2SLS second-stage estimates.

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

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 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 summary, our findings so far indicate that UBB connections positively affect firm-level employment, leading to an increase in average firm size. However, we ask whether this effect is uniform across all workers or varies according to key employee characteristics such as job contract type, age, and skill level. Moreover, we explore whether these heterogeneous effects differ depending on the technological intensity of the firm's activities. We address these questions in the following section.

## 5. Heterogeneity by contract, age, skills, and technology

In this section, we examine potential heterogeneity in the impact of UBB on various types of employment, as well as differences arising from firms' levels of technological intensity.

First, we look at the impact of UBB on firm-level employment 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.

The results reported in Table 6 reveal that the overall positive impact of UBB on employment is not evenly distributed across workforce categories but is driven by specific groups of workers. Our estimates show that firms significantly increase the employment of middle managers (+5.2%) and workers aged over 50 (+9.9%) following the introduction of UBB, with both coefficients statistically significant at the 1% level. In contrast, the employment levels of other worker categories remain largely unaffected, as indicated by the generally smaller and statistically insignificant coefficients associated with UBB in these regressions. These findings align with the hypothesis that advanced digital applications relying on high-speed internet, such as machine learning and artificial intelligence, enhance decision-making processes by analyzing large datasets, identifying patterns, and recommending optimal solutions. Consequently, these technologies exhibit a strong complementarity with managerial roles (Agrawal et al., 2019).

Another key question is whether these heterogeneous effects vary according to the technological intensity of the sector in which a firm operates. To address this, we re-estimate the regressions from Table 6 separately for high-tech and low-tech firms. A detailed list of high-tech sectors is provided in Subsection 2.3. The results of this analysis are presented in Table 7, where Column (1) corresponds to high-tech firms and Column (2) to low-tech firms. As in previous tables, we report the IV estimates.

As shown in the table, the positive impact of UBB on high-level employment identified in Table 6 is more pronounced in high-tech industries, though it remains evident, albeit to a lesser extent, in low-tech sectors. Specifically, among high-tech firms, UBB is associated with an 11% increase in the number of middle managers and a 12.2% rise in workers aged over 50, both statistically significant at the 1% level. In contrast, low-tech firms experience smaller increases of 3.4% for middle managers and 8.2% for older workers following UBB introduction. Notably, within low-tech firms, we also observe a modest negative effect on blue-collar employment, which declines by 3.3% and is significant at the 10% level.

Overall, these results provide a clear affirmative answer to our question: the technological intensity of a firm is a crucial dimension of heterogeneity. The positive impact of UBB on high-level positions is stronger in advanced high-tech sectors, indicating that the complementary effect of UBB on managerial roles intensifies with the technological sophistication of the firm's activities. Conversely, in low-tech firms, alongside a weaker complementarity with high-level positions, we also observe potential substitution effects of UBB on lower-level roles (i.e., blue-collar jobs), consistent with the skill-biased interpretation of the digital divide (Akerman et al., 2015).

Another important question concerns the skill content of jobs. So far, we have identified heterogeneous impacts of UBB by job contract, workers' age, and firms' technological intensity. Yet, within these job categories, which workers are most affected, those with relatively higher or lower skill levels? To address this, we categorize workers within each firm by their relative wage level, which we use as a proxy for skill. As detailed in Section 2, we classify workers as high- or low-wage within each job contract type by comparing their wages to a narrowly defined reference cell. In Table 8, we estimate the impact of UBB rollout using Specification IV1 on eight firm-level worker categories: high- and low-wage blue-collar workers, white-collar workers, middle managers, and top managers (all variables expressed in logarithms). Consistent with Table 7, this analysis distinguishes between high-tech and low-tech firms. The first column reports results for high-tech firms, while the second pertains to low-tech firms.[17]

First, focusing on high-tech firms, the positive impact of UBB rollout on middle managers appears to be concentrated among high-wage middle managers rather than their low-wage counterparts. Our estimates indicate a 4.4% increase in high-wage middle managers following UBB introduction. Notably, we also observe a strong positive effect on high-wage white-collar workers (+11.1%), an impact that was not apparent when considering white-collar workers as a whole. High-wage white-collar workers likely correspond to specialized technicians and professionals. This evidence reinforces the notion of a pronounced complementary effect of UBB on high-level positions within high-tech firms, both managerial roles and highly specialized professional positions, consistent with the task-based framework of skill-biased technical change (Autor et al., 2003).

Among low-tech firms, we observe a somewhat different pattern. First, the positive impact on middle managers primarily occurs among low-wage, rather than high-wage, middle managers, with the former increasing by 2% following UBB introduction. Second, similar to high-tech firms, we find a positive effect of UBB on high-wage white-collar workers, though the magnitude is substantially smaller (+4.7%) compared to high-tech companies. Third, the negative impact on blue-collar workers documented in low-tech firms appears to be driven by high-wage blue-collar workers (-5%), who are likely employed in specialized blue-collar roles. Conversely, low-wage blue-collar workers, typically engaged in elementary occupations such as warehouse work or cleaning, seem unaffected by UBB rollout. These findings suggest that low-tech firms experience more modest complementarities between UBB and high-level positions compared to high-tech firms. At the same time, they face displacement effects among specialized blue-collar jobs. Unlike traditional DT, modern computer applications increasingly perform cognitive tasks previously handled by relatively high-skill workers (Webb, 2019). Tools such as chatbots, voice assistants, autonomous planning and scheduling systems, robots, and autonomous vehicles leverage machine intelligence to sense, reason, and respond to their environment (Verma and Singh, 2022; Duan et al., 2019), which helps explain the substitution effects observed among specialized blue-collar occupations.

## 6. Conclusions

In this paper, we explored the impact of advanced digital technologies on firm-level employment outcomes. We utilized a uniquely rich balanced panel dataset that combined

[17]As explained in Section 2, the high- and low-wage categories correspond to workers whose wages fall above the 75th percentile and below the 25th percentile, respectively, of their relative cell's wage distribution. Workers with wages between the 25th and 75th percentiles are excluded to more clearly capture low- and high-skilled groups. Consequently, results in Table 8 are not directly comparable to those in Table 7.

municipality-level information on ultra-fast broadband (UBB) access with matched employer-employee administrative data covering the entire population of Italian private-sector firms with at least 10 employees. Our empirical strategy exploited the relative distance of each municipality to the nearest backbone node as a plausibly exogenous source of variation.

The results obtained from instrumental variable estimations demonstrated that firms expanded their workforce by 2.7% following the deployment of UBB. When examining the impact across different workforce categories, by job contract, workers' age group, and skill content, we found substantially heterogeneous effects of UBB. Specifically, for high-tech companies, the findings revealed a strong complementary effect of UBB on high-level job positions, evident 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 jobs were relatively modest compared to those in high-tech companies. Importantly, no substitution effects were detected in high-tech sectors, whereas the displacement of high-wage blue-collar workers, consistent with specialized manual jobs, was observed among low-tech firms.

Our results contribute to a deeper understanding of the labor market effects of digital transformation enabled by high-speed broadband, an essential technology supporting key digital tools used by firms, such as cloud-based enterprise software (e.g., ERP, CRM), video conferencing, and real-time data exchange, which transform internal processes, supply chains, and work organization. These developments lay the groundwork for more advanced applications, especially in service-oriented and knowledge-intensive sectors, and are well documented by ISTAT surveys and related empirical research (e.g., DeStefano et al., 2023; Bertschek et al., 2013).

In this context, we find that the expansion of UBB produces heterogeneous effects on firm-level employment. While some displacement occurs in low-tech sectors and among high-wage manual roles, there is a clear pattern of complementarity between digital infrastructure and higher-level jobs, particularly managerial and specialized white-collar positions. These findings contrast with evidence on the effects of first-wave digital technologies, such as automation and industrial robotics, which tended to substitute human labor, including in high-skill occupations held by older, educated workers (Webb, 2019). Moreover, these results have broader implications beyond the specific technologies examined, suggesting that digital innovation tends to reinforce the role of human capital and decision-making functions.

As such, our study provides a valuable empirical benchmark for anticipating how the ongoing integration of more advanced digital systems, such as AI, might interact with organizational structures and occupational dynamics in the future. Further research is needed to clarify their effects on income distribution and inequality, as well as the role of specific job tasks. Notably, our firm-level analysis focuses on the impact of advanced digital technologies on the intensive margin of employment, capturing partial equilibrium effects while abstracting from general equilibrium feedbacks, such as worker migration across locations or sectoral labor demand spillovers. These broader dynamics remain important avenues for future investigation.

## References


Abrardi, L., Cambini, C., Sabatino, L., 2024. The impact of ultra-fast broadband on labor income: An event study approach. Economics of Innovation and New Technology, 33 (8), 1076–1095.

Agrawal, A., Gans, J. S., Goldfarb, A., 2019. Artificial intelligence: The ambiguous labor market impact of automating prediction. Journal of Economic Perspectives 33 (2), 31–50.

Akerman, A., Gaarder, I., Mogstad, M., 2015. The skill complementarity of broadband internet. The Quarterly Journal of Economics 130 (4), 1781–1824.

Angrist, J. D., Pischke, J., 2008. Mostly harmless econometrics. Princeton University Press, Princeton, NJ.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., Van Reenen, J., 2020. The fall of the labor share and the rise of superstar firms. The Quarterly Journal of Economics 135 (2), 645–709.

Autor, D., Levy, F., Murnane, R. J., 2003. The skill content of recent technological change: An empirical exploration. The Quarterly Journal of Economics 118 (4), 1279–1333.

Barth, E., Davis, J. C., Freeman, R. B., McElheran, K., 2023. Twisting the demand curve: Digitalization and the older workforce. Journal of Econometrics 233 (2), 443–467.

Belotti, F., Di Porto, E., Santoni, G., 2021. The effect of local taxes on firm performance: Evidence from geo-referenced data. Journal of Regional Sciences 61 (2), 492–510.

Bertschek, I., Cerquera, D., Klein, G. J., 2013. More bits  more bucks? Measuring the impact of broadband Internet on firm performance. Information Economics and Policy 25 (3), 190–203.

Cambini, C., Grinza, E., Sabatino, L., 2023. Ultra-fast broadband access and productivity: Evidence from italian firms. International Journal of Industrial Organization 86, 102901.

Cambini, C., Sabatino, L., 2023. Digital highways and firm turnover. Journal of Economics and Management Strategy 32 (4), 673–713.

Campante, F., Durante, R., Sobbrio, F., 2017. Politics 2.0: The multifaceted effect of broadband internet on political participation. Journal of the European Economic Association 16 (4), 1094–1136.

Card, D., DiNardo, J. E., 2002. Skill biased technological change and rising wage inequality: Some problems and puzzles. Journal of Labor Economics 20 (4), 733–783.

Czernich, N., Falck, O., Kretschmer, T., Woessmann, L., 2011. Broadband infrastructure and economic growth. The Economic Journal 121 (552), 505–532.

DeStefano, T., Kneller, R., Timmis, J., 2023. Cloud computing and firm growth. The Review of Economics and Statistics,online first.

Duan, Y., Edwards, J., Dwivedi, Y., 2019. Artificial intelligence for decision making in the era of big data evolution, challenges and research agenda. International Journal of Information Management 48, 63–71.

Fabling, R., Grimes, A., 2021. Picking up speed: Does ultrafast broadband increase firm productivity? Information Economics and Policy 57, 100937.

Falck, A., Heimisch-Roecker, A., Wiederhold, S., 2021. Returns to ICT skills. Research Policy 50 (7), 104064.

Falck, O., Gold, R., Heblich, S., 2014. E-lections: Voting behavior and the internet. American Economic Review 104 (7), 2238–2265.

Falck, O., Mang, C., Woessmann, L., 2018. Virtually no effect? Different uses of classroom computers and their effect on student achievement. Oxford Bulletin of Economics and Statistics 80 (1), 1–38.

Forman, C., Goldfarb, A., Greenstein, S., 2012. The internet and local wages: A puzzle. American Economic Review 102 (1), 556–75.

Gaggl, P., Wright, G. C., 2017. A Short-run view of what computers do: Evidence from a UK tax incentive. American Economic Journal: Applied Economics 9 (3), 262–294.

Gavazza, A., Nardotto, M., Valletti, T., 2018. Internet and politics: Evidence from U.K. local elections and local government policies. The Review of Economic Studies 86 (5), 2092–2135.

Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review 104 (8), 2509–2526.

Miner, L., 2015. The unintended consequences of Internet diffusion: Evidence from Malaysia. Journal of Public Economics 132, 66–78.

Nicoletti, G., Von Rueden, C., Andrews, D., 2020. Digital technology diffusion: A matter of capabilities, incentives or both? European Economic Review 128, 103513.

Nucci, F., Pozzolo, A. F., 2010. The exchange rate, employment and hours: What firm-level data say. Journal of International Economics 82 (2), 112–123.

OECD, 2018. Bridging the digital gender divide - Include, upskill, innovate. Tech. rep., Organization for Economic Co-operation and Development, Paris.

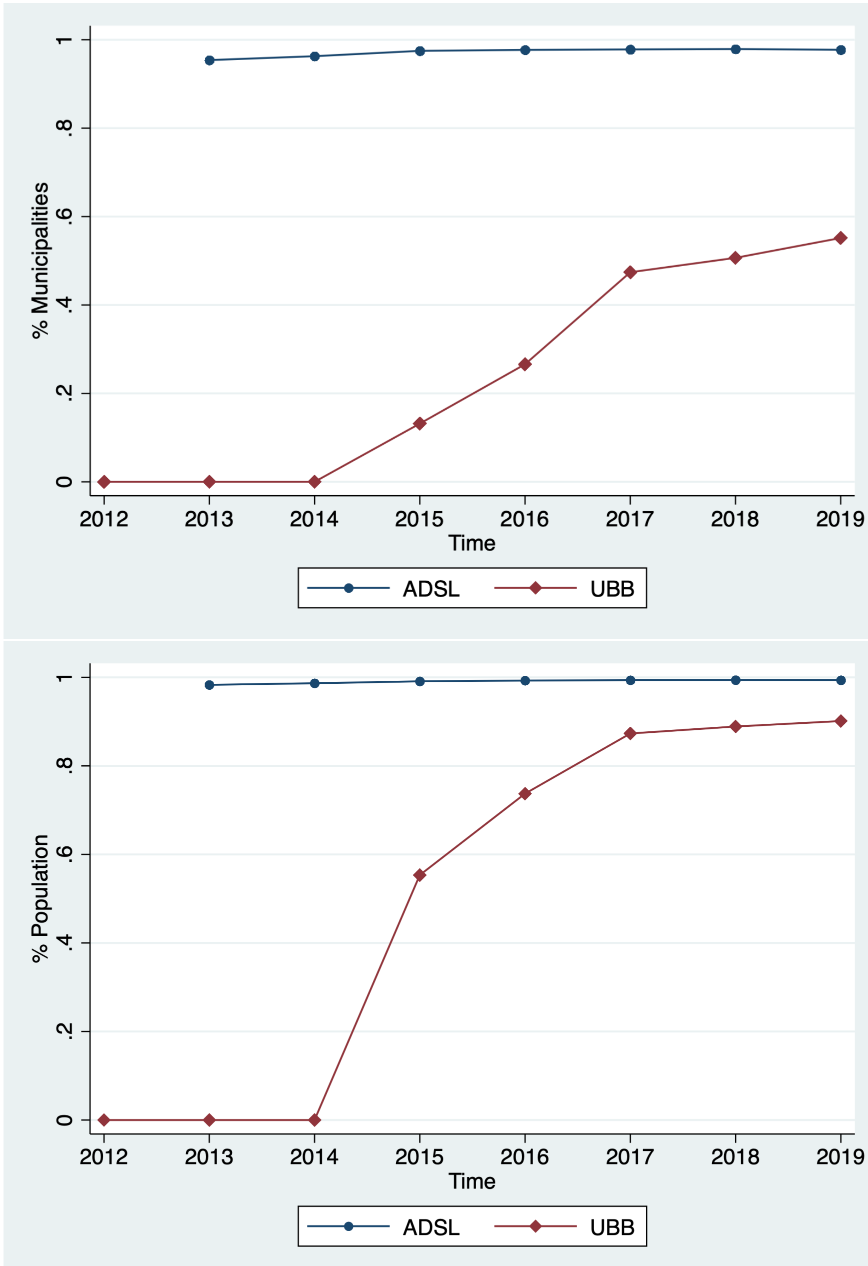
Verma, S., Singh, V., 2022. Impact of artificial intelligence-enabled job characteristics and perceived substitution crisis on innovative work behavior of employees from high-tech firms. Computers in Human Behavior 131, 107215.

Webb, M., 2019. The impact of artificial intelligence on the labor market, unpublished paper.

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 a 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 construction.

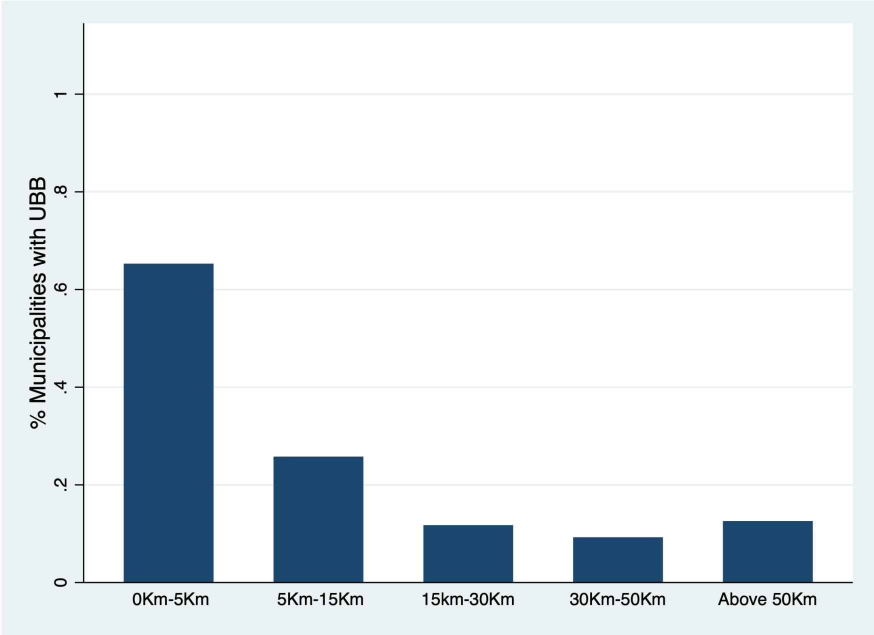
Table 3: **Sample summary statistics: firm-level employment**

| **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 | | | | | |

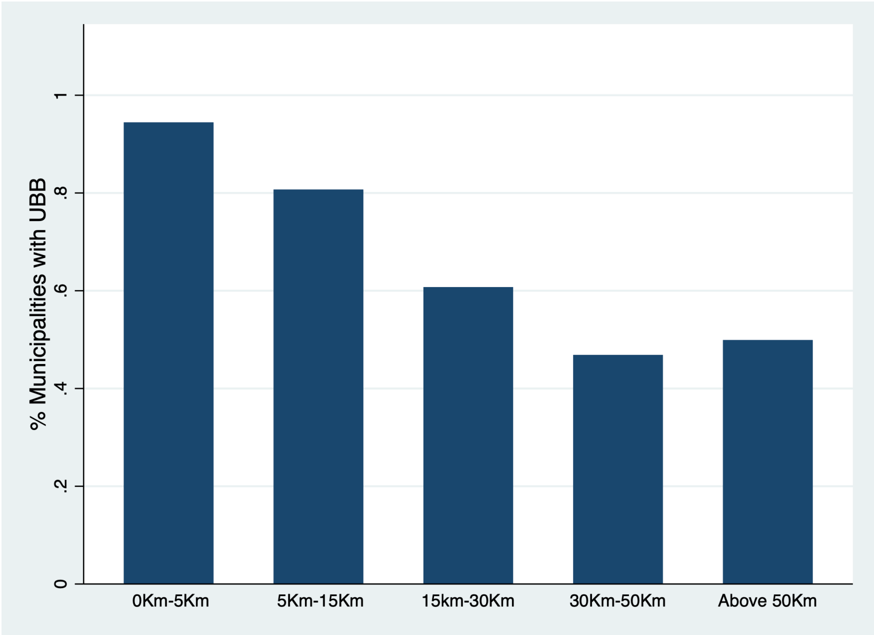
*Source:* UBB-INPS data set (2012-2019).

"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 to 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 to 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

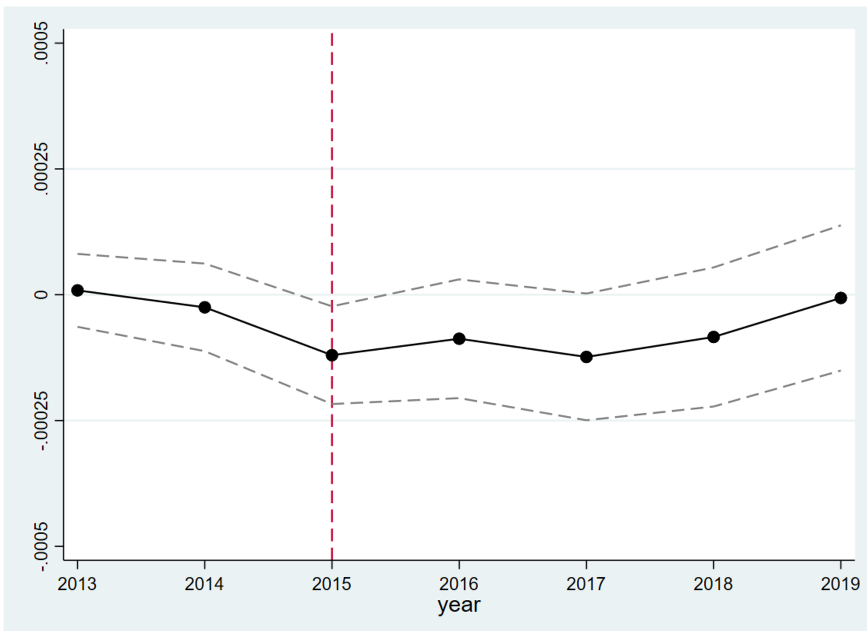
*Source:* UBB data set (2012-2019).
The figure shows the percentage of municipalities with access to UBB for different classes of $OPB_m$. Table 1 reports the list of broadband acronyms and variables, with related descriptions.

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

*Source:* UBB data set.

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

Figure 4: **Parallel trend test in reduced-form regression**




*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 firm-level employment**

| | Dep. var.: $log(employees_{i,m,t})$ | | | |
|---|---|---|---|---|
| | **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 × year dummies | - | yes | yes | yes |
| Cov. 2 × 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 (five 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 that 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" include 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 × year dummies | yes |
| Cov. 2 × 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 firm-level employment by job position and workers' age**

| | |
|---|---|
| *Job position* | |
| 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) |
| *Workers' age* | |
| 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 logarithms) 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 firm-level employment by job position and workers' age in high-tech versus low-tech firms**

| | **High-tech (1)** | **Low-tech (2)** |
|---|---|---|
| *Job position* | | |
| Dep. var.: Blue-collar workers (log) | | |
| $UBB_{m,t}$ | $-0.031$ | $-0.033$* |
| | (0.052) | (0.017) |
| Dep. var.: White-collar workers (log) | | |
| $UBB_{m,t}$ | +0.031 | +0.028 |
| | (0.041) | (0.021) |
| Dep. var.: Middle managers (log) | | |
| $UBB_{m,t}$ | +0.110*** | +0.034** |
| | (0.038) | (0.014) |
| Dep. var.: Top managers (log) | | |
| $UBB_{m,t}$ | +0.020 | +0.006 |
| | (0.021) | (0.007) |
| *Workers' age* | | |
| Dep. var.: Under-29 workers (log) | | |
| $UBB_{m,t}$ | $-0.091$ | $-0.034$ |
| | (0.065) | (0.029) |
| Dep. var.: Workers aged 30-49 (log) | | |
| $UBB_{m,t}$ | +0.019 | $-0.013$ |
| | (0.036) | (0.019) |
| Dep. var.: Over-50 workers (log) | | |
| $UBB_{m,t}$ | +0.122*** | +0.082*** |
| | (0.045) | (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 firm-level employment by wage level in high-tech versus low-tech firms**

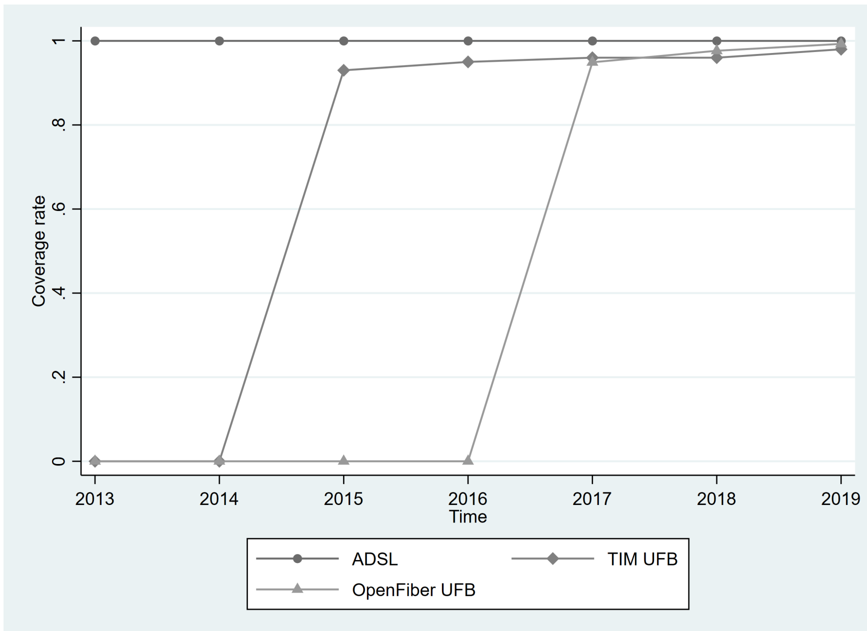
| | **High-tech** (1) | **Low-tech** (2) |
|---|---|---|
| *Skill level by job position* | | |
| Dep. var.: High-wage blue-collar workers (log) | | |
| $UBB_{m,t}$ | $-0.043$ | $-0.050$* |
| | (0.052) | (0.027) |
| Dep. var.: Low-wage blue-collar workers (log) | | |
| $UBB_{m,t}$ | $-0.047$ | $+0.021$ |
| | (0.054) | (0.030) |
| Dep. var.: High-wage white-collar workers (log) | | |
| $UBB_{m,t}$ | $+0.111$** | $+0.047$** |
| | (0.052) | (0.021) |
| Dep. var.: Low-wage white-collar workers (log) | | |
| $UBB_{m,t}$ | $+0.041$ | $-0.013$ |
| | (0.055) | (0.023) |
| Dep. var.: High-wage middle managers (log) | | |
| $UBB_{m,t}$ | $+0.044$* | $+0.002$ |
| | (0.025) | (0.009) |
| Dep. var.: Low-wage middle managers (log) | | |
| $UBB_{m,t}$ | $+0.047$ | $+0.020$** |
| | (0.029) | (0.009) |
| Dep. var.: High-wage top managers (log) | | |
| $UBB_{m,t}$ | $+0.021$ | $-0.004$ |
| | (0.017) | (0.006) |
| Dep. var.: Low-wage top managers (log) | | |
| $UBB_{m,t}$ | $+0.022$ | $-0.002$ |
| | (0.020) | (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

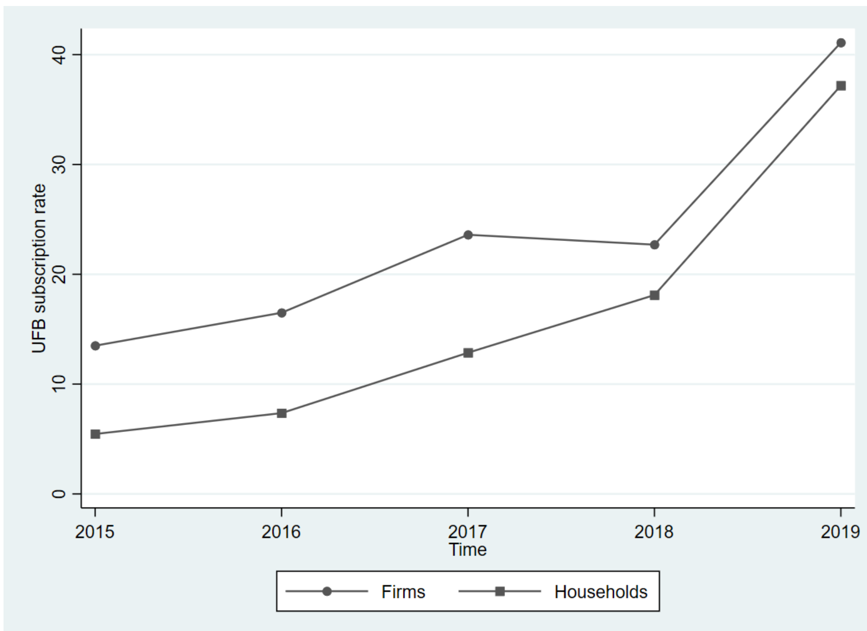
## A. Additional broadband-related information

Figure A.1: **Within-municipality UBB 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: **UBB adoption**




*Source:* European Council and ISTAT.
The UBB subscription rate indicates the percentage of households that subscribed to a UBB connection service. Table 1 reports the list of broadband acronyms and variables, with related descriptions.