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Ultra-Fast Broadband Access and Productivity: Evidence from Italian Firms

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Abstract

We study the impact of ultra-fast broadband (UFB) infrastructures on the total factor productivity (TFP) and labor productivity of firms. We use unique balanced panel data for the 2013-2019 period on incorporated firms in Italy. Using the geographical location of the firms, we match firm data with municipality-level information on the diffusion of UFB, which started in 2015 in Italy. We derive consistent firm-level TFP estimates by adopting a version of the Akerberg et al.'s (2015) method, which also accounts for firm fixed effects. We then assess the impact of UFB on productivity and deal with the endogeneity of UFB by exploiting the physical distance between each municipality and the closest backbone node. Our results show an overall positive impact of UFB on productivity. Services companies benefit the most from advanced broadband technologies, as do firms located in the North-West and South of Italy. We further decompose the impact of full-fiber networks (FTTH) from mixed copper-fiber connections (FTTC) and find that FTTH networks significantly contribute to enhancing firm productivity. Finally, by exploiting Labor Force Survey data, we provide suggestive evidence that productivity increases from UFB might be related to structural changes at the workforce level.

Keywords: Ultra-fast broadband (UFB), fiber-based networks, fiber-to-the-home (FTTH), total factor productivity (TFP), labor productivity.

JEL: L96, D24, D22.

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1. Introduction

After one year of the COVID-19 pandemic and its shattering effects on our economies, on the 9th of March 2021, the European Union (EU) released a new plan to spur digitization and the deployment of digital infrastructures in order to “empower businesses and people in a human-centered, sustainable, and more prosperous digital future”. This plan, named “Digital Compass 2030”, is aimed at stimulating a substantial digital transformation of EU firms and public services.¹ However, such a dramatic change in businesses would only be possible if all the firms and citizens participated in the digital transformation. The EU plan specifically considers the deployment of ultra-fast broadband (UFB) networks as a critical infrastructure to obtain such targets. These networks rely on optical fiber rather than copper wire for the “last mile”. Fiber-based networks are considered the most resilient, secure, and trustworthy infrastructures to support all the emergent digital technologies and they thus represent a key asset for the economic success and recovery of the EU. All across Europe - and particularly in Italy - Next Generation EU funds are largely being devoted to the deployment of UFB infrastructures.²

The goal of this paper is to provide the first quantitative assessment of the impact of UFB investments on the productivity of firms. We focus on firm productivity, that is, on both labor and total factor productivity (TFP), as it is widely recognized as the ultimate engine of growth in today’s global economies (OECD, 2015). The deployment of UFB infrastructures can lead to several effects on economic activities and, in particular, on the productive performance of firms. Productivity may be spurred *via* more efficient business processes, the use of new digital technologies, and the acceleration of innovation enabled by UFB networks. For instance, UFB connections allow the transfer, analysis, and digital storage of larger amounts of better-quality data at a lower cost (Benassi et al., 2021). Moreover, UFB is a key enabling factor for flexible patterns of work, such as teleworking and smart-working, which may be associated with higher productivity (and labor force participation, Akerman et al., 2015). Italy represents an interesting field experiment to evaluate the effects of UFB connections. Starting from 2015, massive investments have been made in UFB infrastruc-

¹The new EU targets are i) at least 75% of EU companies should introduce new digital services, such as cloud computing, artificial intelligence and machine learning, or the use of big data and data analytics, by 2030; ii) at least 90% of EU firms should enhance their (basic) levels of digital intensity and skills. The document can be downloaded here.

²In the introductory part of the 2021 Italian Recovery and Resilience Plan (“Piano Nazionale di Ripresa e Resilienza”), Mario Draghi has written that “*among the causes of the disappointing productivity trend, there is the inability to seize the many opportunities linked to the digital revolution. This delay is due both to the lack of adequate infrastructures and to the Italian industrial structure, which is characterized by a prevalence of small and medium-sized enterprises that have often been slow in adopting new technologies and in moving toward productions characterized by high value added*”. The full text (in Italian) is downloadable here.

tures, mostly driven by the national incumbent telecommunication operator, Telecom Italia Mobile (TIM). Moreover, a new operator (OpenFiber) entered the market in 2017 and has significantly fostered UFB deployment.

We exploit a unique balanced panel data set for the 2013-2019 period, which collects municipality-level information on UFB access matched with firm-level data on Italian private-sector incorporated companies that were active in 2019. Our data are obtained from different sources. First, we have access to TIM and OpenFiber data, and we observe the staggered diffusion of UFB connections for each municipality. We also observe whether each municipality has access to basic fiber connections (FTTC), or to the most advanced full-fiber (FTTH) networks.³ Second, we gather firm-level information from AIDA, a rich data set provided by the Bureau Van Dijk. This data set collects financial and other firm-level information on the Italian companies whose balance sheets are required to be filed with the chambers of commerce (i.e., incorporated companies). We thus match UFB municipal data with firm data by using the operating center location of the firms. Third, we use representative data on Italian private-sector employees from the Labor Force Survey (LFS). Although we do not have firm-level data on the composition of the workforce, LFS allows us to explore the relationship between UFB diffusion and relevant workforce indicators (e.g., based on skills and age) at detailed levels of aggregation. Finally, we retrieve municipality demographics, which we use as controls in the econometric analysis, from the Italian Statistical Office (ISTAT).

The empirical analysis is performed in two steps. The first one recovers measures of firm productivity. The TFP estimates of firms are obtained as the estimation residuals of sector-specific log-linearized value-added production functions. We pay attention to the consistent estimation of TFP by adopting a recent nonparametric method based on Akerberg et al. (2015) and Lee et al. (2019). In particular, our TFP indicators control for the simultaneity of production inputs and explicitly remove unobserved time-invariant firm heterogeneity. We instead computed labor productivity as the logarithm of value added over the number of employees. Labor productivity focuses on one input of the production process (i.e., labor), while TFP provides a commonly used indicator for the overall productive performance of a company (DeStefano et al., 2018; Devicienti et al., 2018; Van Biesebroeck, 2007). In the second step of the empirical analysis, we investigate the impact of UFB access on the TFP and labor productivity of firms. Potential identification issues may arise from the non-randomness of the UFB diffusion process. Unobserved local shocks may affect both the UFB investment

³FTTC refers to “fiber-to-the-cabinet” networks, which involve a first segment of fiber from the local central office to a cabinet near the customers’ premises and then a final segment of copper wire. FTTH stands for “fiber-to-the-home”, in which local central offices and the customers’ premises are fully connected by fiber cables.

decisions and firm productivity, thereby biasing the ordinary least squares (OLS) estimates. To account for such endogeneity concerns, we use an instrumental variable (IV) approach that exploits plausibly exogenous variation in the distance between each municipality and its closest national backbone node (Cambini and Sabatino, 2021; Campante et al., 2017; Miner, 2015). These nodes, called “optical packet backbone” (OPB) nodes, are upgraded facilities of the old telephone communication network constructed around the early 2000s, hence their location can be considered exogenous to the current productivity levels once we account for firm-level fixed effects.

The results suggest an overall positive impact of UFB on firm productivity, in the 2.9-3.8% range, for TFP and labor productivity, respectively. However, such an overall positive impact hides substantial heterogeneities across industry sectors and geographical locations. First, we find that only services companies obtain significant productivity gains from UFB connections. Along the same lines, only firms in the North-West and South of Italy are found to experience significant productivity increases from UFB connections. We then decompose the effect of FTTH from standard UFB connections. Although FTTC infrastructures are found to be significant drivers of firm productivity, the results show an additional positive contribution of the most advanced FTTH networks. Finally, by using LFS data, we provide suggestive evidence that the diffusion of UFB is associated with substantial changes in the composition of the workforce of firms. In particular, we find that the UFB roll-out is related to significant decreases in the share of low-skilled workers employed by firms, as well as a significant increase in the share of young employees. These results are consistent with the existence of a substantial generational and 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.

These results are particularly important for the current policy debate in Europe. The recovery and resilience plans of most EU countries contain relevant public interventions to spread UFB connections. The Italian government, for instance, decided to invest as much as 3.8 billion euros in its national recovery plan to complete the roll-out of FTTH connections, plus 2.9 billion euros to strengthen the digital transformation of firms and public offices. This study presents the first quantitative support to those public policies. Our results show that such plans can have a substantial effect on fostering firm productivity.

The remainder of the paper is organized as follows. Section 2 provides a review of the existing empirical studies on this topic and highlights the contributions of this paper to the extant literature. Section 3 discusses the data and the productivity measures used in the paper in detail and presents preliminary descriptive evidence. Section 4 describes the

empirical setting and the adopted identification strategy. Section 5 presents and discusses the results. Finally, Section 6 concludes and highlights possible avenues for future research.

2. Previous empirical literature and background

The literature on the impact of broadband investments on economic outcomes is extensive.⁴ The analyses range from the impact on GDP growth at national or local levels (Czernich et al., 2011; Kolko, 2012), to labor market outcomes (Forman et al., 2012; Akerman et al., 2015), to educational attainments and political outcomes (Belo et al., 2013; Campante et al., 2017; Gavazza et al., 2018), among others. Almost all these studies focus on standard ADSL-based technologies, whereas only a few of them evaluate the economic effects of investments in UFB infrastructures. Briglauer et al. (2021), for instance, assess the economic benefits of UFB within and across neighboring areas in Germany, and show that an increase in average bandwidth speed by one unit (i.e., 1 Mbit/s) induces a rise in regional GDP of 0.18%. Another recent paper by Cambini and Sabatino (2021) focuses on the impact of UFB on firm turnover in Italy. The authors show that UFB significantly reshapes the national industrial structure by increasing firm exit - particularly that of small enterprises - without significantly affecting firm entry.

A stream of literature investigates the effects of broadband technologies on the performance outcomes of firms. All the extant studies on this topic focus on basic (i.e., ADSL-based) broadband infrastructures and report contrasting results, ranging from positive effects to non-significant ones. Grimes et al. (2012) examine the impact of a firm's ADSL broadband adoption on labor productivity, and find a significantly positive effect of around 7-10%. Similarly, using data from a single Italian administrative region (Trentino-Alto Adige), Canzian et al. (2019) show that ADSL broadband connections are associated with an increase in revenues and total factor productivity (+14.8 and +9.1%, cumulatively over two years), but not with any significant changes in personnel costs or employment levels. On the contrary, Bertschek et al. (2013), who employ firm-level data on Germany to analyze the relationship between the ADSL broadband adoption and changes in labor productivity of firms in the 2001-2003 period, show that basic broadband adoption does not affect firm productivity to any great extent. Colombo et al. (2013) report a similar result for Italian small- and medium-sized enterprises observed over the 1998-2004 period. Using a panel of Irish manufacturing firms, Haller and Lyons (2015) also document a non-significant effect of ADSL broadband adoption on firm productivity. Finally, using cross-sectional firm-level data on the UK, DeStefano et al. (2018) find that ADSL broadband availability significantly affects

⁴See Greenstein (2019) for a detailed literature review.

firm size, but not firm productivity.

We contribute to the existing literature in several ways. First, none of the extant studies look at the effects of the most advanced UFB infrastructures on firm performance. Our paper thus provides the first quantitative assessment of the impact of UFB connections on firm productivity. Second, we explore the presence of heterogeneous patterns in the effect of interest across important firm-level characteristics, including economic sectors and geographical locations. Third, our paper is also the first to empirically disentangle the impact of full-fiber networks from the baseline mixed copper-fiber connections. Finally, we provide suggestive evidence on the underlying dynamics of workforce reconfiguration following UFB deployment as a potential channel for its impact on firm productivity.

3. Data

3.1. Firm-level data and productivity measures

We gather the firm data from AIDA, a large data set provided yearly by the Bureau Van Dijk. AIDA reports detailed financial and other firm-level information on all the (non-agricultural and non-financial) private-sector Italian firms that are required to file their balance sheets with a chamber of commerce (i.e., incorporated companies). Apart from balance-sheet information (e.g., value added, tangible fixed assets, expenditure on intermediate goods), AIDA also provides detailed information on the economic sector of a firm (Ateco 2007 classification), its location, and the number of employees, among others.

First, we select the firms in AIDA that were still active in 2019 (i.e., our last year of observation of UFB deployment; see below). We compute TFP estimates using data from 2010, thereby exploiting all the available years in AIDA in order to compute the firms' TFP more precisely.⁵ This sample of firms, referring to the 2010-2019 period, amounts to slightly fewer than 3 million firm-year observations (after a basic cleaning described below in this subsection).

In order to estimate a firm's TFP, we start by considering the following production function:

$$Y_{it} = f(L_{it}, K_{it}; A_{it}), \quad (1)$$

where the output of firm i at time t (Y_{it}) is modeled as a function of labor (L_{it}) and capital (K_{it}), and A_{it} is the TFP. A_{it} is that part of the output that is not explained by labor and capital inputs, and it can be thought of as a black box containing several aspects of the firm, such as its productive, organizational, and logistic performance. In sum, TFP captures the

⁵AIDA provides a 10-year history from the last available year at the moment of data extraction.

overall productivity level of a firm. We then retrieve the TFP estimates according to:

$$A_{it} = f^{-1}(Y_{it}, L_{it}, K_{it}). \quad (2)$$

In particular, we assume that the production function in Equation (1) is a log-transformed value-added Cobb-Douglas function. A critical and well-known issue in the estimation of production functions is the simultaneity of inputs, that is, inputs are endogenous since they respond to a firm’s productivity level. For example, a highly productive firm will produce more, using more inputs. Similarly, a productivity improvement (e.g., due to the introduction of a process innovation) will lead to an increase in the usage of inputs. This simultaneity problem makes the OLS estimates of the input contributions - and, therefore, of TFP - inconsistent. A fixed effects (FE) estimation (Mundlak, 1961) cannot solve the issue either, although it removes the fixed firm-specific productivity level.⁶ Therefore, a method is needed that can control for a more articulated framework, whereby the unobserved productivity level can fluctuate over time, and production inputs are allowed to respond to such fluctuations.

The control function approach proposed by Akerberg et al. (2015) (ACF, hereafter) represents a solution to the problem of simultaneity. In a nutshell, ACF propose using a firm’s demand for intermediate inputs to proxy for its unobserved productivity level. The rationale is that intermediate inputs can capture unobserved productivity because firms can easily adjust their use of intermediate inputs in response to productivity shocks.⁷ In this paper, we use a modified version of the ACF method, recently developed by Lee et al. (2019) (ACF-FE, hereafter), which extends the ACF procedure to explicitly account for firm fixed effects, whereby firm-specific persistence in productivity levels is accounted for. This is important because substantial and persistent differences in productivity levels have been found ubiquitously in the data (Syverson, 2011). On the one hand, explicitly accounting for firm fixed effects ensures that unobserved time-invariant firm heterogeneity is eliminated. On the other hand, it also improves the ability of the proxy variable to capture and control for the fluctuations in the unobserved productivity levels. The ACF and ACF-FE methods are discussed in Appendix A in detail.

We measure a firm’s output (Y_{it}) with its value added. The labor input (L_{it}) is measured

⁶Such a method would only deliver consistent estimates under two unrealistic assumptions: i) the omitted variable bias is derived exclusively from unobserved time-invariant variables and ii) inputs do not respond to unobserved (by the econometrician) productivity fluctuations.

⁷The ACF estimation method is part of the larger family of the so-called “control function estimators” (CFEs), introduced in the seminal work of Olley and Pakes (1996). CFEs have been and are still widely used in applied studies, and they represent the standard way of estimating firm-level production functions (Akerberg et al., 2015).

by considering the number of employees. We measure capital (K_{it}) by referring to the physical capital stock (i.e., tangible fixed assets), computed through a version of the permanent inventory method (PIM).⁸ The intermediate input demand (used in the ACF-FE method to proxy a firm’s unobserved productivity level) is measured by the intermediate input items of the profit and loss accounts, which include both intermediate goods and services used in the production process. We estimate a separate production function for each economic sector, as defined by the 2-digit Ateco 2007 classification. This allows us to take into account any structural differences in the production processes among different industries. In total, we pursue the ACF-FE estimation of 67 different production functions. All these estimations include year, province, sector (3-digit Ateco 2007), size, and firm age category dummies, and year-sector and year-province interactions. We perform a basic cleaning of the sample by removing observations with missing or non-usable information on the key variables (e.g., number of employees, value added, tangible fixed assets), and (a few) firms belonging to 2-digit sectors with too few observations (which we set below 100). In order to implement the ACF-FE method, we have to focus on firms with at least two consecutive years of observations.

We also compute the labor productivity of the firms from the AIDA data set as the logarithm of value added over the number of employees.

3.2. UFB data and the matching process

Our UFB data come from two main sources. First, we have access to TIM network data, which collect information on the staggered UFB roll-out for the Italian incumbent operator since the introduction of UFB networks in Italy in 2015. We observe which municipalities have access to TIM’s UFB for each year of observation. The second data source comes from OpenFiber, which collects additional information on the municipalities covered by the only alternative UFB operator that entered the market in 2017.

The main variable of interest, $UFB_{m,t}$, is an indicator that takes a value of one if municipality m has access to UFB at time t , and zero otherwise. As mentioned earlier, we also observe which municipalities have access to FTTH connections over time. The $FTTH_{m,t}$ variable thus takes a value of one if municipality m has access to FTTH connections at time t , and zero otherwise. It should be noted that our indicator of UFB (and FTTH) refers to the availability of such connections in a municipality at a certain time. One issue that arises

⁸This version of the PIM, which is implemented by Card et al. (2014), applies a constant depreciation rate equal to 0.05; the benchmark in the first year is given by the book value of tangible fixed assets. As direct information on investments is unavailable in our data, these are computed as the difference between a firm’s fixed assets for two contiguous years.

with this indicator is whether UFB diffusion is correlated with UFB adoption by Italian companies. We report the evolution of UFB subscriptions for both households and firms between 2015 and 2019 in Figure 1. As in Akerman et al. (2015), the pattern in the figure suggests a very marked correlation between UFB household and firm usage, thus indicating that our municipality-level UFB deployment data adequately proxy the supply of UFB connections to firms.

Moreover, we have information available on the location of TIM’s national backbone nodes, that is, large telecommunication infrastructures that reroute the traffic at the national level. From this information, we construct our instrumental variable, OPB_m , which defines the distance (in kilometers) between each municipality and the closest national backbone node (see the discussion in Section 4). We also observe the diffusion of the main UFB input, called “optical line terminal” (OLT), from which we derive the $OLT_{m,t}$ variable. This variable, which is used as a control in our regressions, defines the distance (in kilometers) between each municipality and the closest OLT.⁹

Finally, we obtain demographic information from ISTAT. These variables, used as controls in the regressions, include the current population in municipality m at time t and the degree of urbanization of each municipality in 2011 (this information is obtained from the 2011 Italian Census).

We then match the firm-level data with the municipality-level data by using the information provided by AIDA on the firms’ locations. We use the firms’ operating center locations instead of their registered office locations to match the two data sources, since the former reflects the location in which the firm actually operates more correctly.¹⁰ In sum, by matching our UFB data with the municipality where each firm is located, we are able to identify the firms that have access to UFB at each point in time *versus* firms located in municipalities without UFB connections. The final matched data set, on which we analyze the impact of UFB on firm productivity, is composed of 1,278,284 firm-year observations for a total of

⁹OLTs are the endpoint devices in a passive optical network. Not all municipalities have an OLT installed in their central offices. Since optical cables need to be laid underground from the OLT to the users’ premises, such a distance proxies the deployment costs necessary to provide UFB connections (see Cambini and Sabatino, 2021, for details on the upstream telecommunication infrastructures).

¹⁰One issue that arises with the matching process is caused by the presence of multi-establishment firms, which cannot be allocated to a single municipality. Unfortunately, we cannot directly remove such firms because AIDA does not provide plant-level information. However, we construct a proxy to identify multi-establishment firms on the basis of the presence of consolidated balance sheets and firm size (above 250 employees). We then remove such firms from the estimation sample. The restriction on firm size is also useful because large firms usually have dedicated access to UFB connections, regardless of municipality deployment, which can confound the results. Nonetheless, we include these firms in robustness analyses, and find no significant variations in the results. The results are available upon request.

182,612 firms observed each year from 2013 to 2019.¹¹

3.3. Preliminary descriptive evidence

We present some descriptive evidence relevant to our analysis in this subsection.

Table 1 presents an overall description of our final data set. The number of employees in the average firm is small, around 16, which is consistent with the diffusion of micro and small companies in the Italian industrial structure. The median value of employees is 8, which points to half of the sample being made up of micro firms. The companies obtain around 4.2 million euros on average from the sales of their goods and services (i.e., revenues), but, for half of them, this value is below 1.3 million euros. On average, value added per worker is 62,000 euros per year. We observe that 58.6% of our firm-year observations are covered with UFB connections. However, if we only consider the years following the UFB roll-out, such a percentage increases to 82%. Our sample firms are, on average, 20 years old. Around 31% of them are manufacturing firms, 12% operate in the construction sector, whereas another 26% and 31% belong to the trade and services sectors, respectively. Around one-third of the firms are located in the North-West of Italy (34.6%), 26.4% are in the North-East, and another 20.7% and 18.3% are from the Center and South/Islands macro-areas, respectively.

Figures 2 to 4 refer to firm productivity. Figure 2 shows the evolution of TFP and labor productivity of our sample firms from 2013 to 2019. Productivity growth, although increasing slightly, is sluggish (e.g., around +3.5% cumulatively in our 7-year span for labor productivity), consistently with other recent evidence (Bugamelli et al., 2018). Figure 3 instead shows the evolution of TFP, broken down into the four previously mentioned macro sectors: manufacturing, construction, trade, and services. Although weakly increasing trends can be detected for all the sectors, the TFP levels are somewhat heterogeneous. Services firms display the highest TFP values, whereas manufacturing is characterized by the lowest TFP, with construction and trade sectors lying somewhere in between. Finally, Figure 4 shows the evolution of TFP for each macro-area, as previously defined. As is well known, Italy presents a substantial territorial heterogeneity, also in terms of productive performance of its companies, with the Northern regions in the lead, followed by the Central regions, and finally by the Southern regions (Deleidi et al., 2021). This is evident from the figure, which

¹¹Although we use the 2010-2019 observation years to estimate firm-level TFP, we focus on the 2013-2019 time frame because we do not have data for the early years of many firms. This happens either because those firms were created after 2010, or because some values pertaining to the first years of the panel are missing. By restricting our sample to the 2013-2019 time window, we are able to (i) obtain two years of observation before UFB roll-out, and (ii) keep a significantly large number of firms for which we have TFP estimates for each year of observation. We run robustness checks using the 2012-2019 and 2011-2019 panel data sets, and find no substantial variations in the results. The results are available upon request.

shows North-West and North-East regions have the highest TFP levels, the Center of Italy is somewhere in the middle, and, with a somewhat large gap, the Southern areas have the lowest TFP levels.

Finally, Figure 5 reports the percentage of municipalities with access to different broadband connections (i.e., ADSL, generic UFB, and FTTH) during the 2013-2019 period. First, we can notice that ADSL connections cover almost all the Italian municipalities from the beginning of our time frame. Second, by 2019, UFB covers around 55% of the municipalities, which, however, amounts to about 85% of the Italian population. Finally, only a small proportion of municipalities have access to the most advanced FTTH connections (around 8% by 2019). However, since these are typically large cities and metropolitan areas, this results in almost 40% of the Italian population being covered by FTTH in 2019.

4. Empirical strategy

4.1. Empirical model and identification

In the second step of our empirical analysis, we explore the impact of UFB access on firm productivity. We consider several specifications of the following regression model:

$$productivity_{i,m,t} = \alpha + \beta UFB_{m,t} + \theta X_{m,t} + \tau_t + \mu_i + u_{i,m,t}. \quad (3)$$

The dependent variable, $productivity_{i,m,t}$, is either the estimated ACF-FE TFP ($\hat{A}_{i,m,t}$) or labor productivity. Our variable of interest is $UFB_{m,t}$, the indicator that identifies municipalities with access to UFB connections. The $X_{m,t}$ vector collects municipality-level controls, such as the current population and aforementioned $OLT_{m,t}$ variable. Moreover, we include interactions of baseline municipality characteristics with different time trend functions. These additional covariates allow us to very flexibly control for differential trends in firm productivity based on pre-UFB municipality characteristics.¹² The baseline municipality-level controls include the average productivity and firm size, the number of firms operating in the municipality, all referring to 2013, and the degree of urbanization, which we obtain from the 2011 Italian Census. The time trend functions used to interact the baseline municipality controls are, alternately, (i) a 4th-degree polynomial in time, (ii) a $Post_{2015}$ dummy in addition to the 4th-degree polynomial in time, and (iii) year-specific dummies. τ_t collects region-year and sector-year fixed effects, while μ_i denotes firm-specific fixed effects. Finally, $u_{i,m,t}$ is a mean-zero error term. Throughout the analysis, we cluster standard errors at the

¹²This 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 below).

municipality level, thereby allowing for serial correlation within each municipality.

The empirical model described by Equation (3) resembles an intention-to-treat analysis, such as the one in Akerman et al. (2015), where the staggered roll-out of UFB coincides with the intention-to-treat assignment. The identification of the causal impact of UFB on firm productivity requires such an assignment to be as-good-as-random, conditional on observables. In other words, UFB should be uncorrelated with the error term $u_{i,m,t}$, conditional on the firm- and municipality-level controls included in Equation (3). 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 firm productivity, thus implying that the UFB estimate may be confounded by such an omitted variable bias.¹³

Since UFB deployment is the result of a mixture of private and public investments, it is unclear what the expected sign of the omitted variable bias should be. On the one hand, telecommunication operators could invest first in high-density municipalities, which are typically characterized by a large number of firms and high levels of productivity. This would yield a positive correlation between UFB roll-out and firm productivity, which would, in turn, produce an overestimation of the impact of UFB on firm productivity. On the other hand, specific public programs have been implemented in order to ensure UFB deployment also in depressed geographical areas, which are typically characterized by low levels of firm productivity (particularly in the South of Italy, see Figure 4).¹⁴ This would imply a negative correlation between firm productivity and UFB roll-out, thereby underestimating the true effect of UFB on firm productivity.

We deal with the endogeneity of UFB diffusion by exploiting the incumbent’s upstream telecommunication infrastructure. In particular, we leverage on the geographical location of TIM’s backbone nodes. As mentioned earlier, these are pre-existing facilities of the Italian telecommunication network that were realized at the beginning of the 2000s, so that their location can be considered exogenous to any current contingencies that might affect firm productivity.¹⁵ Thus, we compute the distance, in kilometers, from the closest backbone node (OPB_m) for each municipality and we interact it with a $Post_{2015}$ dummy, which takes the value of one from the starting year of UFB roll-out. Our exclusion restriction assumption

¹³The ACF-FE estimation of TFP carried out in the first step of our procedure does not solve any endogeneity problems related to UFB access in the second step. It instead ensures that a firm’s TFP is consistently estimated.

¹⁴Indeed, in December 2013, the Italian government launched a new public program to cover around 5 million households in 784 municipalities located in Southern regions with UFB connections. Such a program, named “EUROSUD”, covered approximately 40% of the households in those regions. The deployment started in 2015 and finished at the end of 2017, with a public contribution of around 325 million euros. TIM won all the assignments and contributed with an additional 160 million euros.

¹⁵Figure 6 depicts the location of the 35 backbone nodes used in our IV approach.

is that, whatever correlation exists between firm productivity and municipality distance from the closest backbone node, such a correlation is constant around the introduction of UFB.

Our exclusion restriction assumption could be violated by the existence of underlying municipality-level trends correlated with both our instrument and firm productivity. For instance, firms located farther away from OPB nodes may have a different evolution of productivity from those firms relatively closer to OPB nodes for reasons that are unrelated to the UFB roll-out. Therefore, we also control for differential trends in our IV estimates on the basis of the municipality characteristics discussed before (see Cambini and Sabatino, 2021; Campante et al., 2017, for a similar empirical strategy).

We test the validity of our instrument through the following reduced form regression:

$$productivity_{i,m,t} = \alpha + \sum_t \delta_t OPB_m \times year_t + \theta X_{m,t} + \tau_t + \mu_i + e_{i,m,t}, \quad (4)$$

where δ_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 (3). If the correlation between OPB_m and firm productivity is fully driven by UFB roll-out, we should observe no significant correlation before 2015. We thus check whether pre-2015 δ_t 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 close to OPB nodes.

Figure 7 depicts the estimated δ_t with the associated 95% confidence interval, excluding the 2013 baseline year. The main coefficient of interest is the one associated with the 2014 interaction, which is not statistically different from zero at the 95% level, for both TFP (panel a) and labor productivity (panel b). Hence, OPB_m is not correlated with firm productivity before the advent of UFB, 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 productivity and OPB_m after 2015 (Figure 7) and (ii) more distant municipalities are less likely to receive UFB connections, then our estimates can be expected to yield a positive impact of UFB on firm productivity.¹⁶

We then run the same sort of analysis by sector of economic activity. This allows us to check whether our instrument is valid for all the sectors. Moreover, it gives us information on the industries most affected by UFB roll-out. The results are collected in Figure 8 for

¹⁶As 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.

manufacturing (panel a), construction (panel b), trade (panel c), and services (panel d). First, we observe flat trends before 2015 across all the industry sectors. Second, the negative overall relationship between OPB_m and firm productivity documented earlier on appears to be fully driven by the services sector. On the contrary, we do not detect any significant relationship between OPB_m and firm productivity for the other industries.

Finally, the dynamics of the correlation between OPB_m and firm productivity after 2015 is also informative about the timing of the productivity effect of UFB. In particular, the downward shift happens in 2017, two years after the initial introduction of UFB. There are two possible explanations for such an effect. On the one hand, the impact of UFB may take time to materialize, because, for instance, firms adopt UFB-based technologies with a certain delay. On the other hand, since the FTTH deployment started in 2017, the effect may be driven by these connections rather than basic UFB. We shed some light on this issue in Section 5, where we include both basic UFB and FTTH indicators in the empirical model.

5. Results and discussion

5.1. The overall impact of UFB on firm productivity

Table 2 collects the main results concerning the overall impact of UFB on TFP and labor productivity. The table reports two sets of OLS estimates of Equation (3) and three sets of the IV-2SLS estimates. All these estimates control for the population of the municipality (expressed in logarithm) and $OLT_{m,t}$, as well as firm, year-region, and year-sector fixed effects. The first OLS specification (OLS1) only includes the aforementioned controls. The second OLS regression (OLS2) adds the baseline municipality-level controls interacted with a 4th-degree time trend polynomial. As specified in Section 4, these municipality-level controls include the average productivity (expressed in terms of labor productivity), the average size (expressed in terms of employees), the number of firms, all computed for the 2013 baseline year, as well as the level of urbanization obtained from the 2011 Italian census. The first IV specification (IV1) starts from Specification OLS2 and instruments the presence of UFB with our $Post_{2015} \times OPB_m$ instrument. The second IV specification (IV2) adds to Specification IV1 the interaction between the municipality-level controls and a $Post_{2015}$ dummy variable, which further controls for a one-off shift in productivity around the introduction of UFB. Finally, the third IV specification (IV3) non-parametrically controls for the municipality-level factors through interactions with year dummies. Columns 1 to 5 refer to TFP, whereas Columns 6 to 10 pertain to labor productivity as a dependent variable. As mentioned earlier, the standard errors are always clustered at the municipality level.

Focusing on the OLS1 estimates (Columns 1 and 6), we observe a negative and statistically significant (though small) coefficient associated with UFB for both measures of firm

productivity. These estimates suggest a reduction of 0.5% and 0.7% on TFP and labor productivity following the deployment of UFB in the municipality where the firm is located. When controlling for relevant municipality-level differential trends (Columns 2 and 7), the OLS estimates move toward zero and become not statistically significant, thereby suggesting a negative bias from the omitted variables.

Moving to our baseline IV results (Specification IV1; Columns 3 and 8), the estimated coefficients rise, and turn positive and significant. The estimated impact of UFB on firm productivity is in the 2.9%-3.8% range for TFP and labor productivity, respectively. When we insert other controls for differential time trend functions (Specifications IV2 and IV3), the coefficients remain positive and significant, slightly increasing in magnitude.

Table 3 presents the first-stage results of our IV-2SLS estimation, one for each specification. The coefficients associated with the instrument (i.e., $Post_{2015} \times OPB_m$) are negative and significant at the 1% level, as one would expect, with F-test statistics well above the usual threshold levels.

The observed positive effect of UFB deployment on firm productivity could derive from several channels. High-speed connections are at the core of virtually all Fourth Industrial Revolution (4IR) technologies, such as big data analytics, artificial intelligence, robotics, and cloud computing, which have been identified as critical drivers of productivity enhancements (Benassi et al., 2021). Therefore, UFB connections might spur productivity by enabling innovative and more efficient business processes, as well as through the acceleration of product innovations. Relatedly, UFB deployment might result in productivity enhancements from structural reconfigurations of the workforce toward (more productive) high-skilled tasks, a tendency that has been widely documented in recent years following 4IR innovations (Akerman et al., 2015; Card and DiNardo, 2021; Goos et al., 2014).

5.2. Sectoral and geographical heterogeneities

Up to now, the results suggest that UFB connections have a positive and significant impact on firm productivity, that is, on both TFP and labor productivity. However, do the results in Table 2 hide diversified effects across the industry sectors and geographical locations of the firms? In this subsection, we explore whether this is the case. Given the large number of firm-year observations, we perform a separate estimation on each category of interest (i.e., we perform estimations on the split samples), thereby allowing for maximum flexibility. For these (and the following) results, we use Specification IV1, since its associated first-stage is more powerful, as suggested by the higher value of the F-test statistic.

Table 4 shows the diversified impact by industry sector, as defined in Table 1 (i.e., manufacturing, construction, trade, and services). Consistently with the reduced form evidence

presented in Section 4, we detect substantial differences in the impact of UFB on firm productivity across sectors. The estimated coefficients on manufacturing, construction, and trade sectors, although positive, are never statistically significant for either TFP or for labor productivity. Instead, we detect a large and significant positive impact for the services sector, which collects around one-third of our sample firms. The presence of UFB networks is estimated to boost TFP by as much as 5.4% and labor productivity by 8.2% for such companies.

Table 5 evaluates the presence of heterogeneities across the geographical locations of the firms. We divide the companies across the four macro-areas of Italy: North-West, North-East, Center, and Southern regions. We detect substantially diversified effects also in this case. Firms located in the North-West appear to benefit significantly from UFB connections, with estimated effects equal to 4% and 4.5% for TFP and labor productivity, respectively. High coefficients, although showing lower significance levels, are also detected for the firms located in the Southern regions of Italy. In this case, we estimate positive impacts of 9.3% and 11.9% for TFP and labor productivity, respectively.

These additional results thus show the existence of relevant heterogeneities in the impact of UFB on firm productivity. The positive effect on the services sector is consistent with previous evidence on higher broadband penetration in such an industry. As pointed out by Fornefeld et al. (2008), the companies in the services sector are “broadband leaders” in the adoption of online technologies and more prone to using new online business services than other sectors. Consistently, a recent report by ISTAT (2020) shows that companies in the services sector adopt more Internet-based solutions, use more e-commerce for business-to-business transactions (around 70% of all online transactions in Italy in 2020), and create more revenues from online services.

From the geographical perspective, the positive impact detected for North-Western regions is consistent with the idea that firms that perform better are those that benefit the most from the use of advanced information and communication technologies (see Forman et al., 2012, for a similar result for basic broadband networks). The North-West of Italy has historically been the richest and most developed area of the country (Bugamelli et al., 2018), and has consistently displayed the highest mean productivity levels, even before the introduction of UFB (see figure 4). Moreover, ISTAT (2020) highlights a more prominent use of online services by companies in the North-West of Italy. Surprisingly, an economically relevant positive effect is also observed in Southern regions, which instead are those characterized by the lowest average productivity levels. Such a high productivity gain, spurred by UFB connections, might be due to the generally very low starting productivity levels of such firms and their typically underdeveloped production processes. In these contexts, the great

potential of UFB networks - even though not fully exploited (e.g., with the implementation of the most advanced 4IR innovations) - might still have been able to substantially boost productivity.

5.3. Disentangling FTTH from FTTC

So far, we have focused on the impact of UFB infrastructures on firm productivity, regardless of the specific configuration of the network. However, our data set allows us to investigate the contributions of basic UFB and the most advanced FTTH connections to firm productivity. To this aim, we estimate the following regression:

$$productivity_{i,m,t} = \alpha + \beta_1 UFB_{m,t} + \beta_2 FTTH_{m,t} + \theta X_{m,t} + \tau_t + \mu_i + v_{i,m,t}, \quad (5)$$

where $FTTH_{m,t}$ is an indicator that takes the value of one if municipality m at time t has access to FTTH services, and zero otherwise, while $v_{i,m,t}$ is the usual mean-zero error term. Since, as usual, $UFB_{m,t}$ switches to one for the presence of any ultra-fast configuration, the β_1 coefficient captures the impact of FTTC. When municipality m has access to FTTH connections, then $FTTH_{m,t}$ is also equal to one, so that the effect of FTTH on firm productivity is given by $\beta_1 + \beta_2$. Therefore, β_2 captures the additional effect on firm productivity stemming from access to the most advanced FTTH, compared to basic UFB connections.

Equation (5) suffers from the same previously described endogeneity issue. However, we now have two potentially endogenous variables, namely, $UFB_{m,t}$ and $FTTH_{m,t}$, so that at least two instrumental variables are needed. In order to consistently identify β_1 and β_2 , we use the interactions between OPB_m and the year dummies from 2015 onward as instruments. Given the flat trends before 2015 observed in the reduced form analysis, we can use those interactions as instruments in a 2SLS-IV estimation of Equation (5). In short, we use the same source of exogenous variation, namely, the distance from the closest national backbone node. However, while the instrument $Post_{2015} \times OPB_m$ captures a one-off shift on firm productivity induced by UFB, in this setting, the instruments allow for a more flexible dynamics after 2015.

We know, from Table 2, that there is a positive overall effect of UFB on firm productivity. Moreover, Figure 7 suggests that its effect takes time to materialize. The question is whether this lagged effect is driven by basic UFB, or whether the shift that we observe in 2017 derives from the introduction of FTTH. Table 6 collects the estimated 2SLS-IV coefficients for $UFB_{m,t}$ and $FTTH_{m,t}$. The results show that basic UFB is the main driver of the observed positive overall impact. The estimated β_1 referring to TFP is positive, equal to 0.022, and statistically significant. A similar pattern is observed for labor productivity, with an estimated β_1 equal to 0.031 and significant at the 1% level. Moreover, FTTH

connections also appear to be important sources of productivity gains. Having access to FTTH connections, rather than just to basic UFB is estimated to potentiate the effect by an additional 1.2% for TFP and 1.5% for labor productivity.

Overall, these results highlight that, although basic UFB connections are relevant drivers of firm productivity, further investments in more advanced UFB infrastructures, such as FTTH, significantly amplify the positive effects on enterprises.

5.4. *Potential mechanisms and underlying trends*

How are firms facing the advent of UFB networks? Recent empirical evidence has shown that the radical innovations encompassed within 4IR are leading to dramatic changes in the way firms operate, starting from the management of their human resources. In this respect, firms are undergoing substantial reconfigurations of their workforce in favor of employees whose skills are complementary with the new technologies, that is, high-skilled workers (Akerman et al., 2015; Card and DiNardo, 2021).

Although we do not have firm-level information on the workforce composition, we are nonetheless able to explore whether such a dynamics also emerges following the introduction of UFB networks by resorting to worker-level data. In particular, we exploit LFS, a representative survey on Italian workers provided yearly by ISTAT, which collects rich information on the characteristics of the workers, their jobs, and the firms they work in. We use LFS data from 2014, one year before the introduction of UFB, to 2019. From the worker-level LFS data, we construct the (aggregate) share of low-skilled workers compared with high-skilled workers for each administrative region (20 classes), sector of economic activity (9 classes), firm size class (4 categories), and year. This variable thus provides an indicator of the workforce composition in terms of skills in each region-sector-size combination for each year.¹⁷ Correspondingly, we compute a measure of UFB networks at the regional level. This measure is defined as the share of municipalities in each administrative region covered by UFB, weighted by the municipality population (i.e., it expresses a coverage rate).

We then estimate the relationship between UFB coverage and workforce skill composition through the following simple regression:

$$y_{r,s,d,t} = \alpha + \gamma UFB_{r,t} + \rho Z_{r,s,d,t} + \psi_{r,s,d,t}, \quad (6)$$

¹⁷We compute this share for each cell as the ratio between the number of low-skilled workers over the total number of workers in the cell. Low-skilled occupations include blue-collar workers and apprentices, whereas high-skilled occupations refer to white-collar workers, middle managers, and top managers. Moreover, it should be noted that the version of LFS available to the public does not provide information on the municipality of the firm where the worker is employed. It only provides the administrative region, which we use to construct the cells.

where $y_{r,s,d,t}$ is the share of low-skilled workers compared with high-skilled workers in region r , sector s , firms of size d , and year t ; $UFB_{r,t}$ is our regional-level indicator of UFB coverage in year t ; $Z_{r,s,d,t}$ is a set of fixed effects for macro-area, sector, firm size, and year; and, finally, $\psi_{r,s,d,t}$ is the mean-zero error term.

Table 7 (first panel) collects the OLS estimate of $UFB_{r,t}$ as in Equation (6). The estimated coefficient is negative and significant at the 1% level, thus pointing to a negative correlation between the diffusion of UFB and the share of low-skilled workers employed by companies. This result points to an ongoing process of substitution of low-skilled workers with high-skilled workers following the deployment of UFB networks, which is consistent with the presence of complementarities between high-skilled occupations and UFB networks.

Although skills play a critical role in the ability of firms to exploit the advantages offered by new technologies (including UFB), age could also represent a relevant dimension. Indeed, there is strong evidence of a substantial generational divide (in favor of younger individuals) in the capability of using new technologies (OECD, 2018). We thus analyze whether substitution effects emerge in this respect with a regression similar to Equation (6). Again exploiting the LFS data, we estimate the relationship between UFB coverage at the regional level and the share of younger workers (i.e., under-45) in each administrative region, sector, and firm size combination, as previously defined.

Table 7 (second panel) shows the results of this test. The estimated coefficient associated with $UFB_{r,t}$ is positive and significant at the 1% level, thus pointing to a positive relationship between UFB diffusion and the presence of younger workers in companies. Although of a preliminary nature, this result provides suggestive evidence that firms might also be undergoing significant changes in their workforce composition in terms of age, possibly as a consequence of the greater ability of younger workers to exploit the potential of UFB connections.

6. Conclusions

In this paper, we have explored the impact of advanced information and communication technologies on firm productivity. We leveraged on a uniquely rich data set, which collects granular information on UFB access matched with firm-level data, from which we obtained consistent estimates of TFP and computed labor productivity of the firms. Our empirical strategy exploited the relative distance between each municipality and the closest national backbone node as a source of plausibly exogenous variation.

We have found an overall positive and economically relevant impact of UFB on firm productivity, as captured by both TFP and labor productivity. However, we detected the presence of substantial heterogeneities across industry sectors and geographical locations. We

only found large and significant impacts in the services sector, which, nonetheless, constitutes the predominant sector in the Italian economy, accounting for around 70% of the total employment. This result is consistent with the documented higher penetration of digital technologies in the services sector, whereby these companies appear to be more able to grasp the benefits offered by advanced online solutions. As far as the geographical location is concerned, we found that the North-West and South of Italy are the macro-areas that have obtained the greatest benefits from UFB, in terms of productivity gains. Interestingly, these two areas are somewhat different. On the one hand, the North-West of Italy has historically been (and still is) the richest and most productive area of the country, whereas the South encompasses the most underdeveloped regions in Italy and displays the lowest productivity levels. These effects may be explained by two different mechanisms. On the one hand, the effect of the North-West is coherent with the idea that the more advanced and productive firms are more able to exploit the advantages offered by digital technologies (e.g., implementation of 4IR innovations enabled by UFB networks). On the other hand, the effect on Southern companies might emerge because of the generally (very) low starting productivity levels. Even though not associated with the use of cutting-edge technologies, reaching faster broadband connections partially financed with *ad hoc* public programs may have substantially increased the efficiency of the daily operations a firm needs to comply with in the new digital scenario.

Thanks to unique information on the roll-out of both basic UFB (i.e., FTTC) and the most advanced FTTH networks, we have also investigated whether the detected positive impact of UFB on firm productivity is engendered by the former or the latter type of network. We found evidence that basic UFB connections are critical drivers of productivity gains for the firms, but FTTH connections give an additional boost to productivity. This result is important, given the current efforts and investments of both public and private agents in FTTH deployment. From this perspective, our results provide support for the current Italian public policy as outlined in the Italian Recovery and Resilience Plan. The goal of achieving a complete national coverage with full-fiber connections before the end of 2026 seems a good policy tool to boost firm productivity and, thus, aggregate productivity.

Finally, by resorting to worker-level survey data obtained from LFS, we detected the presence of a substantial reallocation of the workforce of firms toward more skilled and younger individuals. This evidence, although of a preliminary nature, points to an ongoing structural process whereby firms reshuffle their workforce to adapt to the dramatic changes and challenges new technologies (including, UFB) imply. On the one hand, UFB entails the use of new technologies that are complementary with high-skilled workers. On the other hand, firms need individuals who have the necessary capabilities to use digital technologies,

and these workers are generally - apart from being skilled - young. Further research with matched employer-employee data could further strengthen the validity of these predictions.

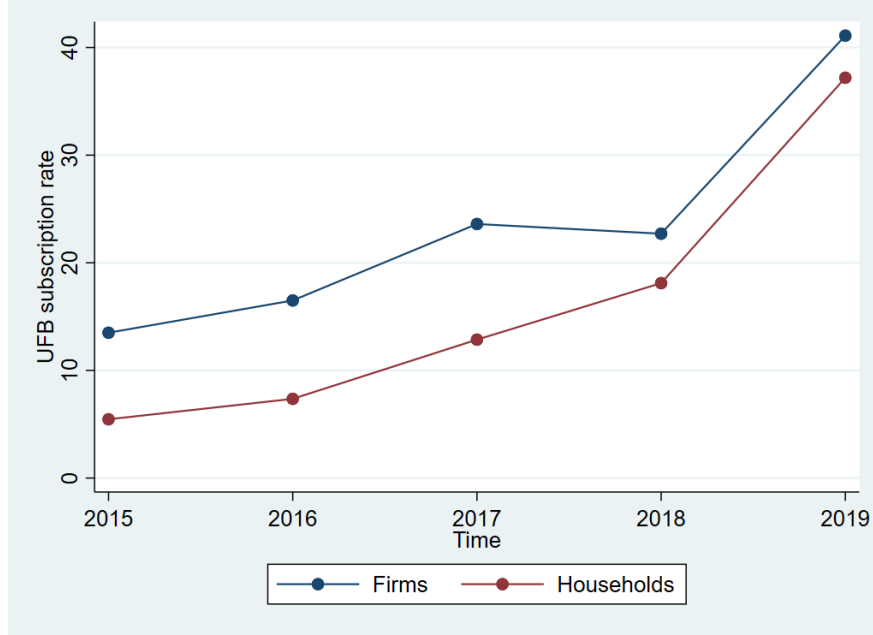
References

- Akerberg, D. A., Caves, K., Frazer, G., 2015. Identification Properties of Recent Production Function Estimators. *Econometrica* 83 (6), 2411–2451.
- 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.
- Belo, R., Ferreira, P., Telang, R., 2013. Broadband in School: Impact on Student Performance. *Management Science* 60 (2), 265–282.
- Benassi, M., Grinza, E., Rentocchini, F., Rondi, L., 2021. Patenting in 4IR Technologies and Firm Performance. *Industrial and Corporate Change*, Online first.
- 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.
- Briglauer, W., Dürr, N., Gugler, K., 2021. A Retrospective Study on the Regional Benefits and Spillover Effects of High-Speed Broadband Networks: Evidence from German Counties. *International Journal of Industrial Organization* 74, 102677.
- Bugamelli, M., Lotti, F., Amici, M., Ciapanna, E., Colonna, F., D’Amuri, F., Giacomelli, S., Linarello, A., Manaresi, F., Palumbo, G., Scoccianti, F., Sette, E., 2018. Productivity Growth in Italy: A Tale of a Slow-Motion Change, *Questioni di Economia e Finanza (Occasional Papers)* - Banca d’Italia - Eurosystem, No. 422.
- Cambini, C., Sabatino, L., 2021. Digital Highways and Firm Turnover, Unpublished manuscript.
- Campante, F., Durante, R., Sobbrío, F., 2017. Politics 2.0: The Multifaceted Effect of Broadband Internet on Political Participation. *Journal of the European Economic Association* 16 (4), 1094–1136.
- Canzian, G., Poy, S., Schüller, S., 2019. Broadband Upgrade and Firm Performance in Rural Areas: Quasi-Experimental Evidence. *Regional Science and Urban Economics* 77, 87–103.
- Card, D., Devicienti, F., Maida, A., 2014. Rent-Sharing, Holdup, and Wages: Evidence from Matched Panel Data. *The Review of Economic Studies* 81 (1), 84–111.

- Card, D., DiNardo, J. E., 2021. Skill Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles, NBER Working Paper, No. 8769.
- Colombo, M. G., Croce, A., Grilli, L., 2013. ICT Services and Small Businesses' Productivity Gains: An Analysis of the Adoption of Broadband Internet Technology. *Information Economics and Policy* 25 (3), 171–189.
- Czernich, N., Falck, O., Kretschmer, T., Woessmann, L., 2011. Broadband Infrastructure and Economic Growth. *The Economic Journal* 121 (552), 505–532.
- Deleidi, M., Paternesi Meloni, W., Salvati, L., Tosi, F., 2021. Output, Investment and Productivity: The Italian North-South Regional Divide from a Kaldor-Verdoorn Approach. *Regional Studies*, Online first.
- DeStefano, T., Kneller, R., Timmis, J., 2018. Broadband Infrastructure, ICT Use and Firm Performance: Evidence for UK firms. *Journal of Economic Behavior & Organization* 155, 110–139.
- Devicienti, F., Grinza, E., Vannoni, D., 2018. The Impact of Part-Time Work on Firm Productivity: Evidence from Italy. *Industrial and Corporate Change* 27 (2), 321–347.
- Forman, C., Goldfarb, A., Greenstein, S., 2012. The Internet and Local Wages: A Puzzle. *American Economic Review* 102 (1), 556–75.
- Fornefeld, M., Delaunay, G., Elixmann, D., 2008. The Impact of Broadband on Growth and Productivity. Tech. rep., European Commission, Brussels.
- 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.
- Greenstein, S., 2019. Digital infrastructure. In: Glaeser, E. L., Poterba, J. M. (Eds.), *Economics of Infrastructure Investment*. University of Chicago Press, Chicago, IL.
- Grimes, A., Ren, C., Stevens, P., 2012. The Need for Speed: Impacts of Internet Connectivity on Firm Productivity. *Journal of Productivity Analysis* 37 (2), 187–201.
- Haller, S. A., Lyons, S., 2015. Broadband Adoption and Firm Productivity: Evidence from Irish Manufacturing Firms. *Telecommunications Policy* 39 (1), 1–13.

- ISTAT, 2020. Le Imprese Usano il Web ma solo le Grandi Integrano Tecnologie più Avanzate. Tech. rep., Italian National Institute of Statistics, Rome.
- Kolko, J., 2012. Broadband and Local Growth. *Journal of Urban Economics* 71 (1), 100–113.
- Konings, J., Vanormelingen, S., 2015. The Impact of Training on Productivity and Wages: Firm-Level Evidence. *The Review of Economics and Statistics* 97 (2), 485–497.
- Lee, Y., Stoyanov, A., Zubanov, N., 2019. Olley and Pakes-Style Production Function Estimators with Firm Fixed Effects. *Oxford Bulletin of Economics and Statistics* 81 (1), 79–97.
- Miner, L., 2015. The Unintended Consequences of Internet Diffusion: Evidence from Malaysia. *Journal of Public Economics* 132, 66–78.
- Mundlak, Y., 1961. Empirical Production Function Free of Management Bias. *Journal of Farm Economics* 43 (1), 44–56.
- OECD, 2015. The Future of Productivity. Tech. rep., Organization for Economic Co-operation and Development, Paris.
- OECD, 2018. Bridging the Digital Gender Divide - Include, Upskill, Innovate. Tech. rep., Organization for Economic Co-operation and Development, Paris.
- Olley, S. G., Pakes, A., 1996. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica* 64 (6), 1263–1297.
- Syverson, C., 2011. What Determines Productivity? *Journal of Economic Literature* 49 (2), 326–365.
- Van Biesebroeck, J., 2007. Robustness of Productivity Estimates. *The Journal of Industrial Economics* 55 (3), 529–569.

Figure 1: UFB adoption



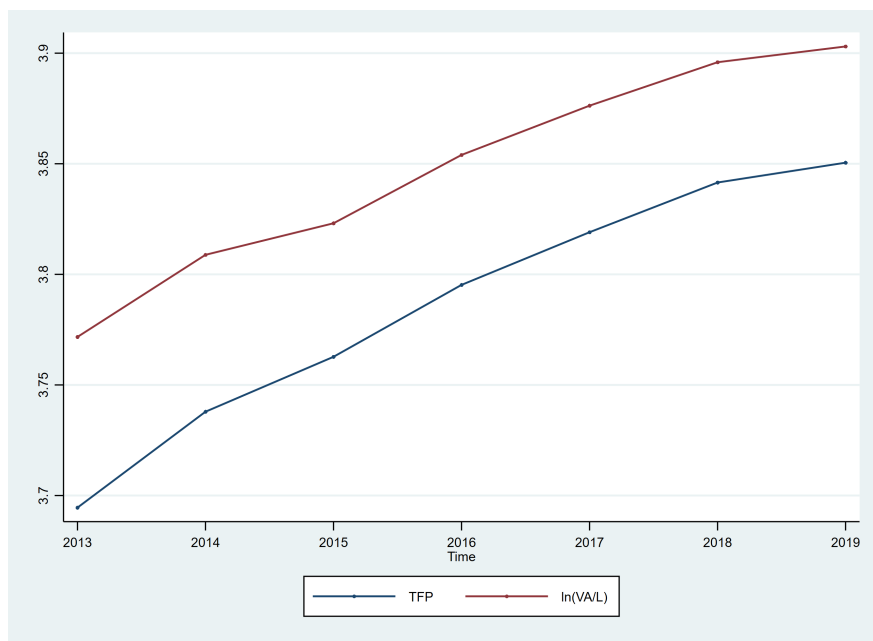
Source: European Council and Italian Statistical Office (ISTAT).

Table 1: Sample summary statistics

Variable	Mean/ percentage	Std. dev.	25th percentile	median	75th percentile
Employees	15.869	31.722	4	8	16
Revenues (1,000 euros)	4,182.906	18,466.670	566	1,266	3,263
Value added (1,000 euros)	975.925	2,864.083	165	363	852
Capital (1,000 euros; PIM)	1,037.714	9,362.723	28.381	118.655	553.822
Expenditure on intermediate inputs (1,000 euros)	2,258.042	15,762.440	92	377	1,343
Firm age (years)	19.685	13.381	9	17	28
Value added over employees (VA/L; 1,000 euros)	61.912	189.936	32.667	46.059	65.5
$\ln(VA/L)$ (labor productivity)	3.848	0.659	3.486	3.830	4.182
$\hat{A}_{i,m,t}$ (ACF-FE TFP; log)	3.786	0.659	3.396	3.772	4.157
$UFB_{m,t}$ (%)	58.6	-	-	-	-
$FTTH_{m,t}$ (%)	14.7	-	-	-	-
OPB_m (km)	24.750	23.978	4.022	19.775	37.193
Manufacturing (%)	30.9	-	-	-	-
Construction (%)	11.9	-	-	-	-
Trade (%)	26.0	-	-	-	-
Services (%)	31.2	-	-	-	-
North-West (%)	34.6	-	-	-	-
North-East (%)	26.4	-	-	-	-
Center (%)	20.7	-	-	-	-
South and Islands (%)	18.3	-	-	-	-
Observations: 1,278,284					
Firms: 182,612					

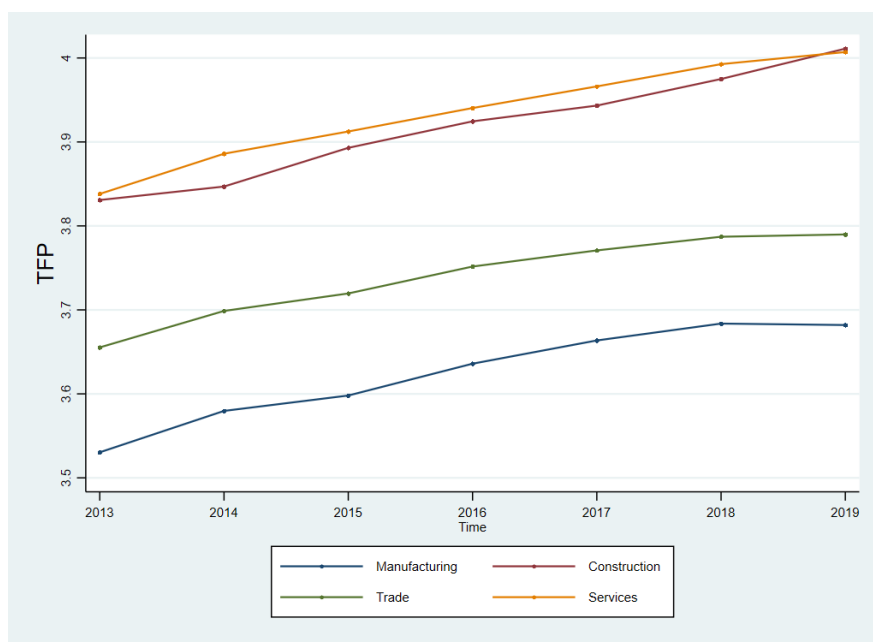
Source: UFB-AIDA data set (for 2013-2019).

Figure 2: **Evolution of TFP and labor productivity**



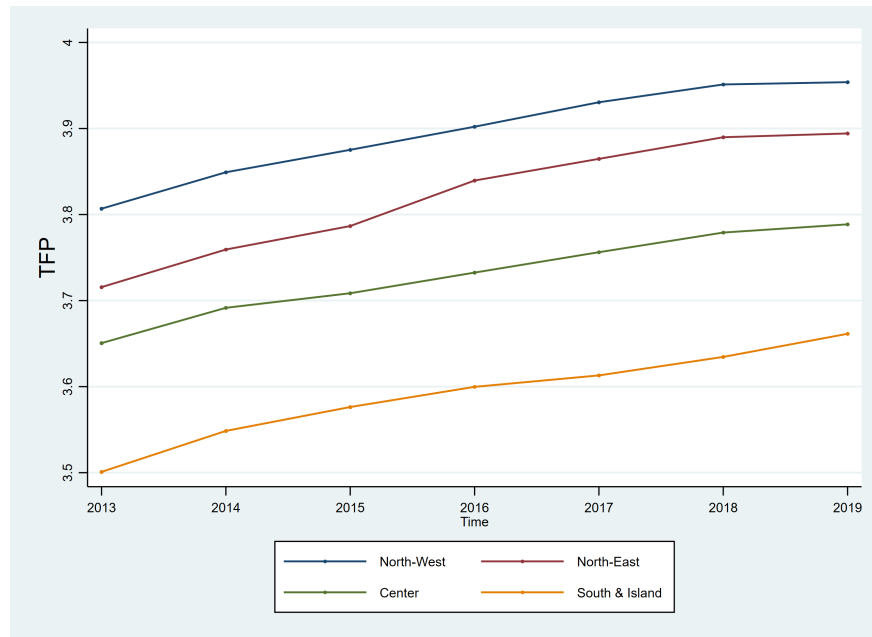
Source: UFB-AIDA data set (for 2013-2019).

Figure 3: **Evolution of TFP by sector**



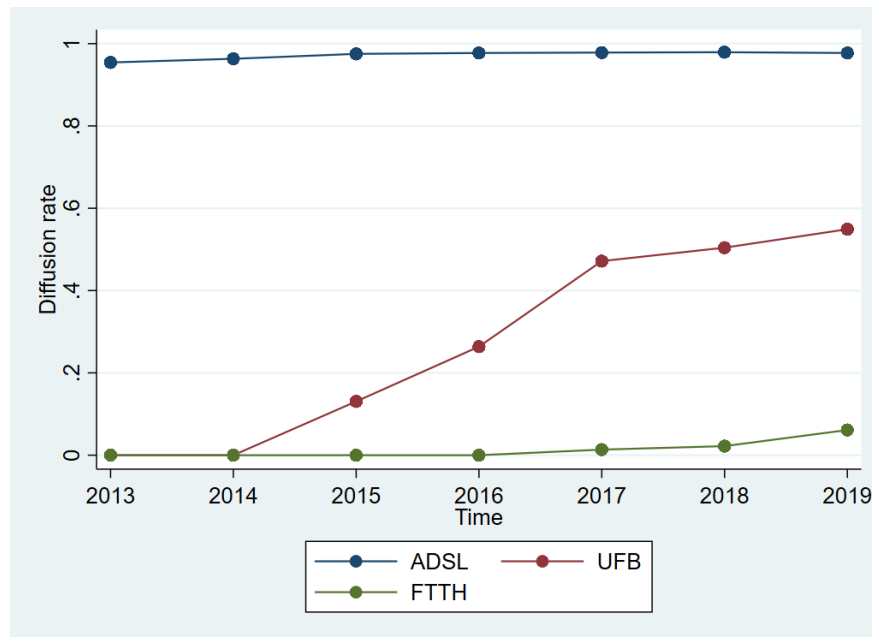
Source: UFB-AIDA data set (for 2013-2019).

Figure 4: **Evolution of TFP by macro-area**



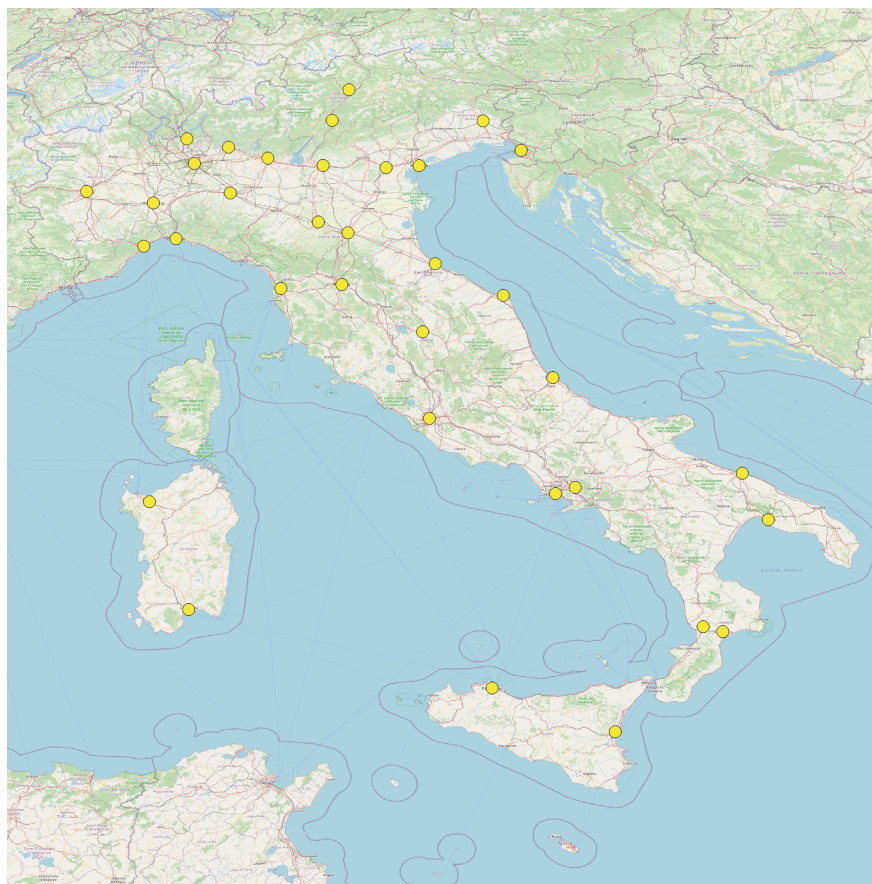
Source: UFB-AIDA data set (for 2013-2019).

Figure 5: **Broadband connection diffusion**



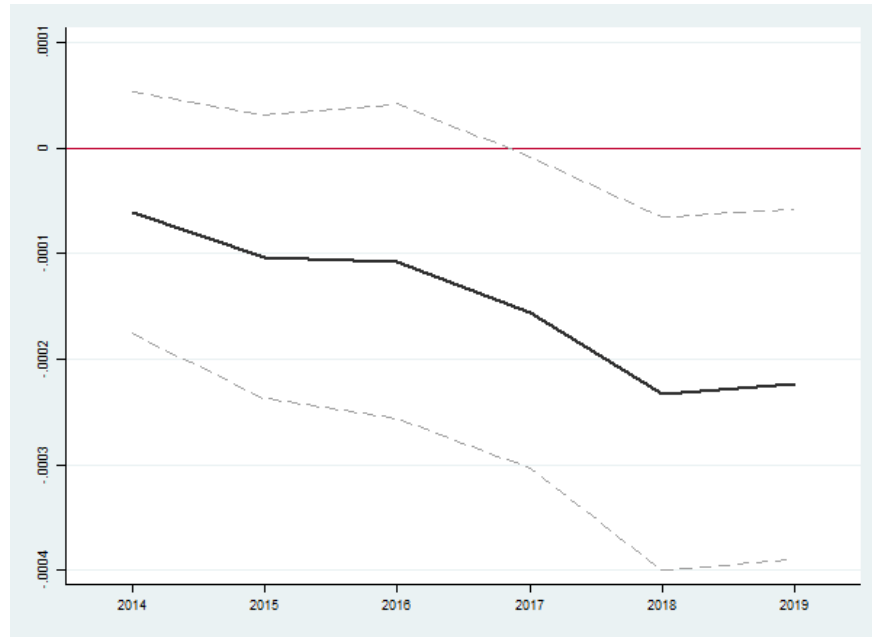
Source: UFB-AIDA data set (for 2013-2019).

Figure 6: Location of the optical backbone nodes

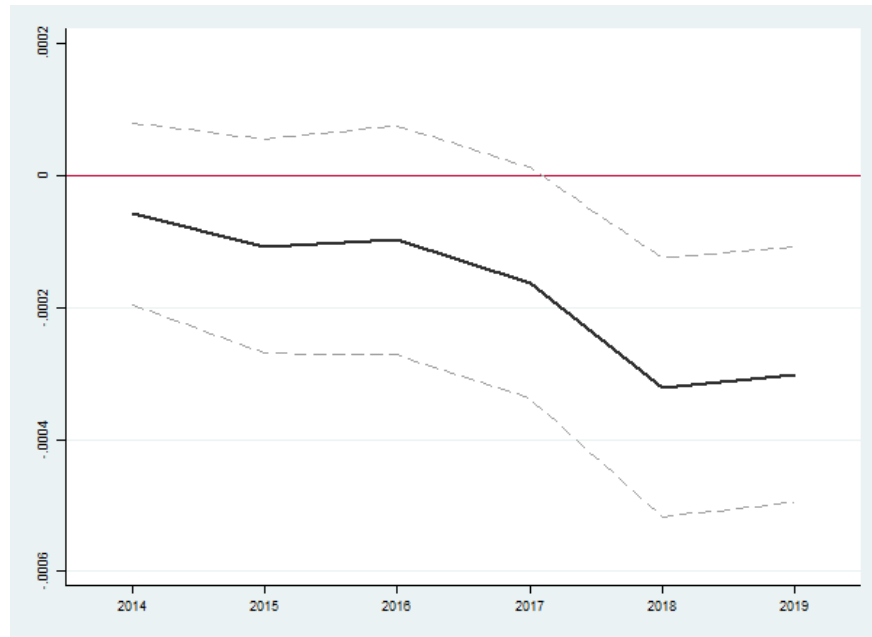


Source: UFB-AIDA data set (for 2013-2019).

Figure 7: **Reduced form evidence; overall effect**



(a) TFP

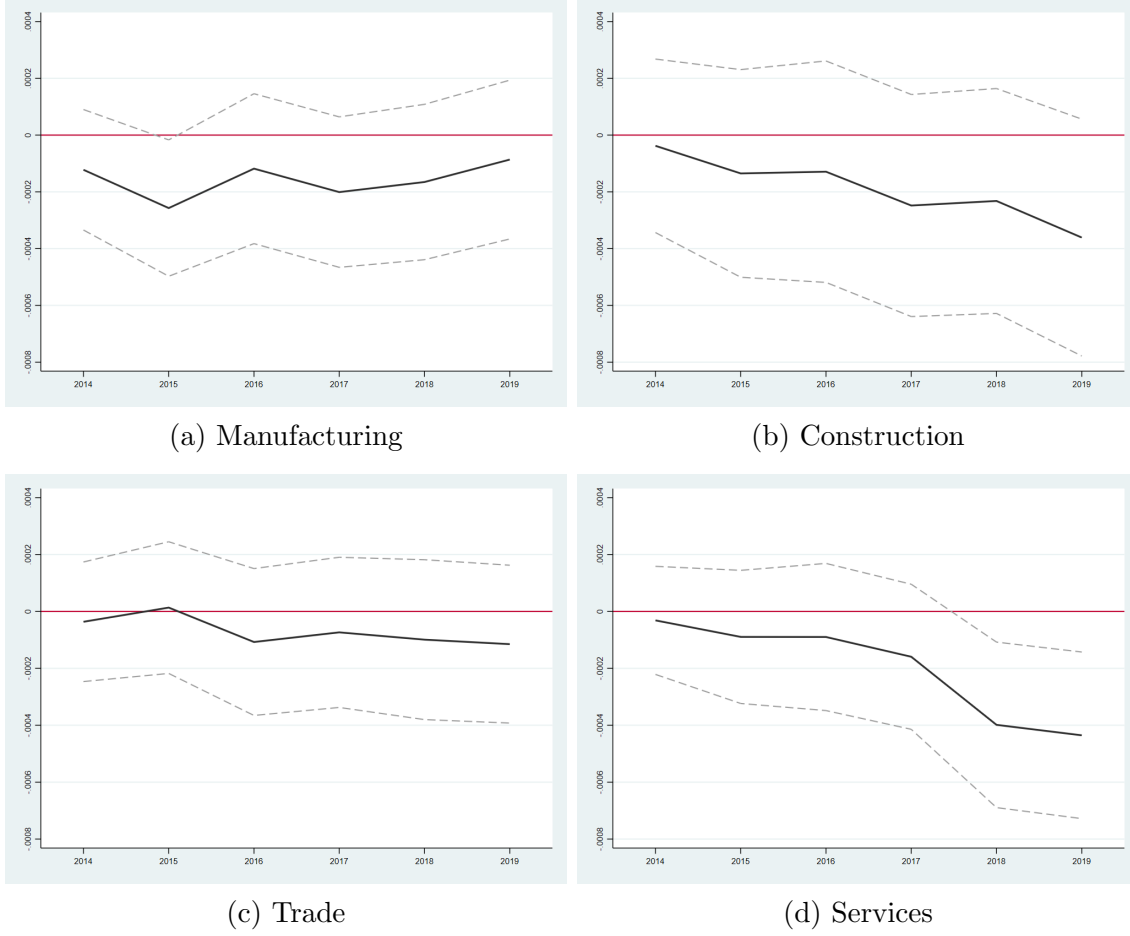


(b) Labor productivity

Source: UFB-AIDA data set (for 2013-2019).

The thick lines represent the estimated OPB_m coefficients interacted with time dummies; the dashed lines represent 95% confidence intervals. Reference year: 2013.

Figure 8: Reduced form evidence; by sector (TFP)



Source: UFB-AIDA data set (for 2013-2019).

The thick lines represent the estimated OPB_m coefficients interacted with time dummies; the dashed lines represent 95% confidence intervals. Reference year: 2013.

Table 2: The overall impact of UFB on productivity

Variable	Dep var.: $\hat{A}_{i,m,t}$ (ACF-FE TFP)				Dep var.: $\ln(VA/L)$ (labor productivity)					
	OLS1 (1)	OLS2 (2)	IV1 (3)	IV2 (4)	IV3 (5)	OLS1 (6)	OLS2 (7)	IV1 (8)	IV2 (9)	IV3 (10)
$UFB_{m,t}$	-0.005*** (0.001)	-0.002 (0.001)	+0.029** (0.014)	+0.044** (0.022)	+0.044** (0.022)	-0.007*** (0.002)	-0.003 (0.002)	+0.038** (0.016)	+0.055** (0.027)	+0.054** (0.027)
Population (log)	-0.019 (0.035)	+0.066* (0.039)	+0.027 (0.043)	+0.004 (0.050)	+0.005 (0.050)	-0.113** (0.054)	+0.029 (0.042)	-0.021 (0.049)	-0.047 (0.059)	-0.046 (0.059)
$OLT_{m,t}$	-0.000 (0.000)	+0.000*** (0.000)	+0.000*** (0.000)	+0.000*** (0.000)	+0.000*** (0.000)	-0.000 (0.000)	+0.000*** (0.000)	+0.000*** (0.000)	+0.000*** (0.000)	+0.000*** (0.000)
Covariates X trend	-	yes	yes	yes	-	-	yes	yes	yes	-
Covariates X post	-	-	-	yes	-	-	-	-	yes	-
Covariates X year dummies	-	-	-	-	yes	-	-	-	-	yes
Year-region dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year-sector dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
First-stage F-test:	-	-	127.670	69.060	69.251	-	-	127.670	69.060	69.251
Observations:	1,278,284									

Source: UFB-AIDA data set (for 2013-2019).

The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. The covariates include: (i) the average labor productivity of the firms in the municipality; (ii) the average number of employees of the firms in the municipality; (iii) the number of firms in the municipality; and (iv) the degree of urbanization of the municipality (three categories: high-density, low-density, and rural). (i), (ii), and (iii) are computed for the 2013 baseline year from our UFB-AIDA data set. (iv) is obtained from Census data and refers to 2011.

Table 3: 2SLS first-stage regressions

Variable	Dep. var.: $UFB_{m,t}$		
	(1)	(2)	(3)
$Post_{2015} \times OPB_m$	-0.004*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
Population (log)	+1.132*** (0.152)	+1.278*** (0.156)	+1.282*** (0.156)
$OLT_{m,t}$	-0.005*** (0.000)	-0.004*** (0.000)	-0.004*** (0.000)
Covariates X trend	yes	yes	-
Covariates X post	-	yes	-
Covariates X year dummies	-	-	yes
Year-region dummies	yes	yes	yes
Year-sector dummies	yes	yes	yes
Firm fixed effects	yes	yes	yes
R-squared	0.838	0.846	0.846
First-stage F-test	127.670	69.060	69.251
Observations: 1,278,284			

Source: UFB-AIDA data set (for 2013-2019).

The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote, the 1%, 5%, and 10% significance levels, respectively. For other information, see the footnote to Table 2.

Table 4: The impact of UFB on productivity by sector

	Dep var.: $\hat{A}_{i,m,t}$ (ACF-FE TFP)	Dep var.: $\ln(VA/L)$ (labor productivity)
Manufacturing		
$UFB_{m,t}$	+0.020 (0.017)	+0.025 (0.018)
First-stage F-test: 148.091		
Observations: 395,178		
Constructions		
$UFB_{m,t}$	+0.047 (0.035)	+0.060 (0.039)
First-stage F-test: 104.748		
Observations: 151,473		
Trade		
$UFB_{m,t}$	+0.011 (0.024)	-0.004 (0.026)
First-stage F-test: 104.539		
Observations: 332,892		
Services		
$UFB_{m,t}$	+0.054** (0.026)	+0.082** (0.035)
First-stage F-test: 111.024		
Observations: 398,741		

Source: UFB-AIDA data set (for 2013-2019).

IV estimates (Specification IV1 of Table 2). The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. For other information, see the footnote to Table 2.

Table 5: The impact of UFB on productivity by geographical area

	Dep var.: $\hat{A}_{i,m,t}$ (ACF-FE TFP)	Dep var.: $\ln(\text{VA}/L)$ (labor productivity)
North-West		
$UFB_{m,t}$	+0.040*** (0.015)	+0.045*** (0.016)
First-stage F-test: 39.375		
Observations: 442,785		
North-East		
$UFB_{m,t}$	-0.038 (0.026)	-0.049 (0.031)
First-stage F-test: 34.542		
Observations: 337,393		
Center		
$UFB_{m,t}$	+0.019 (0.020)	+0.020 (0.023)
First-stage F-test: 28.599		
Observations: 264,432		
South and Islands		
$UFB_{m,t}$	+0.093* (0.048)	+0.119** (0.057)
First-stage F-test: 46.183		
Observations: 233,674		

Source: UFB-AIDA data set (for 2013-2019).

IV estimates (Specification IV1 of Table 2). The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. For other information, see the footnote to Table 2.

Table 6: Disentangling the impact of FTTH

	Dep var.: $\hat{A}_{i,m,t}$ (ACF-FE TFP)	Dep var.: $\ln(\text{VA}/L)$ (labor productivity)
$UFB_{m,t}$	+0.022** (0.010)	+0.031*** (0.011)
$FTTH_{m,t}$	+0.012* (0.007)	+0.015* (0.008)
First-stage F-test: 33.227		
Observations: 1,278,284		

Source: UFB-AIDA data set (for 2013-2019).

IV estimates (Specification IV1 of Table 2). The standard errors, reported in parentheses, are clustered at the municipality level. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. For other information, see the footnote to Table 2. Note that $FTTH_{m,t}$ measures the *additional* impact of FTTH connections from standard UFB connections (i.e., FTTC).

Table 7: UFB and workforce-level dynamics

Dep. var.: Share of low-skilled workers	
$UFB_{r,t}$	-0.098*** (0.018)
Observations: 3,547	
Dep. var.: Share of young workers	
$UFB_{r,t}$	+0.017*** (0.002)
Observations: 3,563	

Source: UFB-AIDA-LFS data set (for 2014-2019).

The robust standard errors are reported in parentheses. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. The unit of observation of the dependent variables is the administrative region (20 classes), the firm size (4 classes), the sector (9 classes), and the year (6 years, from 2014 to 2019). $UFB_{r,t}$ refers to the average $UFB_{m,t}$ within each administrative region and for each year, weighted by the population of the municipality. The controls in both regressions include dummies for the macro-area (4 classes), firm size, sector, and year.

Appendices

A. Estimation of TFP

We here present a discussion on our empirical framework in the context of ACF and ACF-FE estimations. For details on the underlying assumptions - which we summarize here - and their implications, the reader may refer to Akerberg et al. (2015) and Lee et al. (2019).

We estimate the following production function:

$$Y_{it} = A_{it} L_{it}^{\beta_l} K_{it}^{\beta_k}. \quad (\text{A.1})$$

We model the residual productivity, A_{it} , as:

$$A_{it} = \exp\{\alpha + \omega_{it} + \epsilon_{it}\}, \quad (\text{A.2})$$

where α is the average productivity of the firms; ω_{it} is the time- and firm-specific (i.e., idiosyncratic) productivity level; whereas ϵ_{it} is a transitory shock.^{A.1}

In practice, the production function that we estimate is obtained by using Equation (A.2) and by taking logs in Equation (A.1):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it}, \quad (\text{A.3})$$

where lowercase letters indicate natural logarithms.

First, it is assumed that the firm's information set at t , I_{it} , includes both the current and past productivity levels, $\{\omega_{i\tau}\}_{\tau=0}^t$, but not the future productivity levels, $\{\omega_{i\tau}\}_{\tau=t+1}^{\infty}$. Furthermore, it is assumed that the transitory shock, ϵ_{it} , is not predictable by the firm (i.e., $E[\epsilon_{it}|I_{it} = 0]$).

Second, it is assumed that the unobserved productivity level, ω_{it} , evolves according to the distribution:

$$p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it}), \quad (\text{A.4})$$

which is known to the firm. Equation (A.4) expresses the concept that the productivity level evolves according to a first-order Markov process.

These two assumptions imply that it is possible to decompose ω_{it} into its conditional

^{A.1}For the sake of simplicity, we omit the terms that include the basic control dummies (i.e., year, province, sector, size, firm age category dummies, as well as year-sector and year-province interactions) from Equation (A.2). The ω_{it} term thus reflects the unobserved firm-specific productivity level once these fixed effects, which may be correlated with the inputs, are removed.

expectation at $t - 1$ and an innovation term:

$$\omega_{it} = E[\omega_{it}|I_{it-1}] + \xi_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it} = g(\omega_{it-1}) + \xi_{it},$$

where, by construction, $E[\xi_{it}|I_{it-1}] = 0$. Hence, $g(\omega_{it-1})$ is that part of ω_{it} that the firm can predict at $t - 1$, whereas ξ_{it} is the innovation in ω_{it} , observed by the firm at t and, by construction, not predictable at $t - 1$. In practice, firms observe ω_{it} at t and construct expectations on ω_{it} at $t - 1$ by using $g(\cdot)$.

An example may help to clarify this framework. Let us suppose that a firm is experiencing a productivity boom, that is, a series of positive productivity shocks. This is compatible with, for instance, any technological progress introduced into the firm (e.g., a new process technology). The set of assumptions outlined above imply that the firm knows the past and current productivity enhancements it is experiencing. It also implies that the firm is able to predict, with a certain degree of error, the next period's productivity level on the basis of the current productivity level.

Third, it is assumed that firms accumulate capital according to:

$$k_{it} = \kappa(k_{it-1}, i_{it-1}),$$

where investments i_{it-1} are chosen at $t - 1$. This implies that the firm decides upon the level of capital to use at t one period earlier, at $t - 1$ (i.e., $k_{it} \in I_{it-1}$). This assumption entails that it takes a full period for new capital to be ordered, delivered, and installed. Moreover, it implies that capital has dynamic implications (i.e., the firm's choice of capital for period t has an impact on the firm's future profits). We assume that labor at t is chosen as capital, one period earlier, thereby allowing it to have dynamic implications. This assumption is consistent with the presence of significant labor market rigidities in the Italian labor market (e.g., rigid employment protection legislation) and is often adopted in the literature (see, for instance, Konings and Vanormelingen, 2015).

Fourth, it is assumed that the firm's demand for intermediate inputs, m_{it} , is a function of labor, capital, and the firm's unobserved productivity level:

$$m_{it} = f(l_{it}, k_{it}, \omega_{it}) \tag{A.5}$$

Lastly, it is assumed that the function in Equation (A.5) is strictly increasing in ω_{it} . Conditional on labor and capital, the higher the unobserved productivity level is, the larger the demand for intermediate inputs.

At this point, ACF outline a two-step estimation method. Given the assumptions dis-

cussed above, f can be inverted to deliver an expression of ω_{it} , which is unobservable, as a function of l_{it} , k_{it} , and m_{it} , which are instead observable:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, m_{it}).$$

The inverted intermediate input demand function $f^{-1}(\cdot)$ is the key to CFEs: it allows us to “control” for the unobserved productivity level once it is plugged into the production function. Hence, substituting $f^{-1}(\cdot)$ in Equation (A.3) results in the following first-stage equation:

$$\begin{aligned} y_{it} &= \alpha + \beta_l l_{it} + \beta_k k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \\ &= \Phi(l_{it}, k_{it}, m_{it}) + \epsilon_{it} \end{aligned} \quad (\text{A.6})$$

As is common in the literature, we proxy the $f^{-1}(\cdot)$ function with a third-order polynomial in l_{it} , k_{it} , and m_{it} (Akerberg et al., 2015). The β_l and β_k parameters are clearly not identified at this stage and are subsumed in $\Phi(l_{it}, k_{it}, m_{it}) = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it}$. However, the estimation of (A.6) produces an estimate $\tilde{\Phi}(l_{it}, k_{it}, m_{it})$ of $\Phi(l_{it}, k_{it}, m_{it})$.^{A.2} Given the guesses of β_l and β_k , denoted as β_l^* and β_k^* , respectively, it is possible to recover the implied ω_{it} , $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*)$ ^{A.3}, as:

$$\tilde{\omega}_{it}(\beta_l^*, \beta_k^*) = \tilde{\Phi}(l_{it}, k_{it}, m_{it}) - \beta_l^* l_{it} - \beta_k^* k_{it}. \quad (\text{A.7})$$

As ω_{it} is assumed to follow a first-order Markov process (i.e., $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$) and given $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*)$, it is possible to compute the implied innovations, $\tilde{\xi}_{it}(\beta_l^*, \beta_k^*)$, as the residuals of a regression of $\tilde{\omega}_{it}(\beta_l^*, \beta_k^*)$ on $g(\tilde{\omega}_{it-1}(\beta_l^*, \beta_k^*))$. Following the standard practice, we proxy the function $g(\cdot)$ with a third-order polynomial in $\tilde{\omega}_{it-1}(\beta_l^*, \beta_k^*)$ (Lee et al., 2019). The second step of the procedure now recovers the parameters of interest by evaluating the sample analogues of the moment conditions that stem from the previously stated timing assumptions:

$$\begin{aligned} \frac{1}{N} \frac{1}{T} \sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*) k_{it} &= 0 \\ \frac{1}{N} \frac{1}{T} \sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*, \theta^*, \gamma^*) l_{it} &= 0 \end{aligned} \quad (\text{A.8})$$

The search continues over β_l^* and β_k^* until the $\tilde{\beta}_l$ and $\tilde{\beta}_k$ that satisfy Equation (A.8) are

^{A.2}Note that these are just the predicted values from the regression in Equation (A.6).

^{A.3}They also include the constant term α , which eventually does not matter.

found. These are the ACF estimates of β_l and β_k .

The ACF-FE estimator involves only a minimal modification of the standard ACF method, which can be outlined as follows. All the assumptions of ACF are maintained, except for the assumption on the stochastic process that regulates unobserved productivity, which is generalized in the ACF-FE setting. In particular, ω_{it} is assumed to follow a first-order Markov process conditional on a time-invariant random variable η_i :

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}, \eta_i] + \xi_{it}, \quad (\text{A.9})$$

where $E[\xi_{it}|\omega_{it-1}, \eta_i] = 0$ and $E[\epsilon_{it}|\eta_i] = 0$. In particular, Lee et al. (2019) consider a version of Equation (A.9) where $E[\omega_{it}|\omega_{it-1}, \eta_i] = \eta_i + g(\omega_{it-1})$, which results in:

$$\omega_{it} = \eta_i + g(\omega_{it-1}) + \xi_{it}. \quad (\text{A.10})$$

The first step of the ACF-FE procedure, for the above specification of ω_{it} , is the same as in ACF, except for the addition of the fixed-term effect η_i . It is still possible to estimate $\Phi(\cdot)$ from the analogue of Equation (A.6) with added firm fixed effects. In the second stage, it is possible to estimate β_l and β_k proceeding as before, but this time including η_i in the stochastic process of the unobserved productivity level, as defined in Equation (A.10), thereby recovering the implied ω_{it} as in (A.7) and then the implied ξ_{it} as the residuals from a fixed effects regression of $\tilde{\omega}_{it}$ on $g(\tilde{\omega}_{it-1})$, with $g(\cdot)$ being approximated with a third-order polynomial (Lee et al., 2019).