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Work from home and Firm Productivity: The Role of ICT and Size*

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Abstract

Using administrative firm-level data covering the universe of remote workers in Italy, and leveraging exogenous pre-pandemic variation in firm-specific access to fibre broadband as an instrument, this paper investigates the impact of post-pandemic adoption of work from home (WFH) on firm productivity. We find that WFH had a large negative impact on productivity during the pandemic. However, larger firms and those with prior ICT investments mitigated these losses. In the longer term, the impact of WFH is no longer significant. Yet, we find suggestive evidence that firms employing highly qualified workers experienced productivity gains.

Keywords: work from home; firms; productivity.
JEL: D22; J21; J24; L25; O33

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1 Introduction

The rise of work-from-home (WFH) represents a global technological and organisational shift triggered by the COVID-19 pandemic (Juhász, Squicciarini, & Voigtländer, 2020). Recent studies indicate that the adoption of WFH practices has stabilised at levels significantly higher than those before the pandemic, indicating a lasting transformation of the workplace in advanced economies.[1] However, the impact of WFH on firm productivity remains unclear, with existing studies finding both positive and negative effects (Angelici & Profeta, 2024; Bloom, Han, & Liang, 2022; Emanuel & Harrington, 2024; Gibbs, Mengel, & Siemroth, 2023; Yang et al., 2022). Moreover, these studies focus on a single company or group of workers, neglecting the potentially heterogeneous effects of WFH adoption. This gap is important, as larger and better-managed firms are typically more able to capitalise on new technologies (Bloom, Sadun, & Reenen, 2012).

The first objective of this paper is to examine the impact of WFH on firm productivity. To achieve this, we draw on previously unexplored firm-level administrative data covering the entire population of remote workers in Italy.[2] We address the endogeneity of WFH adoption by instrumenting it with firm-specific access to high-speed fibre broadband, a technological prerequisite for remote work. The effect of WFH adoption is estimated by comparing firms within the same local labour market and narrow industry, with and without broadband access, over the three years following the pandemic (2020, 2021 and 2022). The findings indicate significant negative effects in 2020, which become statistically insignificant in the subsequent years.

A second objective is to document the cross-firm heterogeneous effects to shed light on

[1] Barrero, Bloom, and Davis, 2023 show that the proportion of full paid workdays conducted from home in the United States increased from around 5% in 2019 to approximately 25% in 2023. Similarly, Crescenzi, Martino, and Rigo, 2025 leverages the *Labour Force Survey* to document that the share of workers engaged in full or hybrid WFH rose from 10% in 2019 to 25% in 2022 in European countries.

[2] By law, Italian employers must communicate remote working arrangements to ensure insurance coverage for work-related injuries occurring outside the employer's premises. This system has been continuously in place since 2017 through an online declaration. Failure to provide such communication is punishable by an administrative fine. For further details on the legal framework, as well as a validation exercise, see Appendix Section D.1.

the mechanisms through which remote work affects firm operations. Our analysis shows on a subsample of firms that pre-pandemic investments in information and communication technologies (ICTs) mitigated the negative short-term impact of WFH, while the presence of highly qualified employees helped firms sustain productivity gains in the longer term.[3] Lastly, larger firms were also able to offset the negative short-term effects of WFH adoption and to achieve productivity gains beyond the pandemic period.

To tease out the causal impact of WFH, we exploit the pre-pandemic cross-sectional variation in the local availability of fibre technology among Italian firms. Unlike ADSL, the previous technology available in Italy, fibre broadband supports the high-bandwidth activities and scalability essential for effective remote working, such as simultaneous videoconferencing and high-volume data transfer. Therefore, only firms with access to fibre technology were able to effectively transition to WFH during the initial lockdown in 2020. The impact of WFH is estimated by comparing changes in firm-level outcomes before and after the pandemic outbreak and between firms that adopted WFH and those that did not. By comparing firms within travel-to-work-areas and narrow industries, this empirical framework allows us to isolate the specific contribution of WFH to firm performance and productivity amid other confounding factors.

Our identification strategy relies on a massive public investment implemented by the Italian Government in 2015, namely the 'National Ultra-Broadband Plan' (NUBP), aimed at ensuring 100% fibre coverage by 2020. In order to cover the whole territory in a relatively short period, whilst minimising public spending, the NUBP was implemented progressively in adjacent territories. Although the infrastructure rollout might be targeted towards economically growing areas or top-performing firms, we provide evidence that the NUBP's deployment was not influenced by pre-pandemic characteristics or trends of firms or areas. Since our analysis is conducted by comparing firms within Italian travel-

[3] We conduct this latter set of analyses on the subsample of firms that we can match to proprietary data from *Spiceworks* and web-scraped data from *LinkedIn*. To document coverage, we report checks comparing the full sample with the matched subsample in Sections D.4 and D.6.

to-work areas (TTWAs), we are able to control for a wide range of potential unobservable geographical determinants of the broadband roll-out.[4] Moreover, since firms that incur the cost of relocation rarely move with such a short distance as to remain within the same TTWA, this strategy allows us to control for selection into treatment. Lastly, we focus on the broadband supply measure, rather than measuring its actual consumption, allowing us to bypass the endogeneity that may characterise the internet usage measures frequently used in the literature. Collectively, our findings suggest that the broadband rollout was independent of firm or local area characteristics and can be considered as good as random.

We find an average short-term negative effect of WFH on firms' labour productivity and total factor productivity (TFP) growth in 2020. This finding aligns with (Gibbs, Mengel, & Siemroth, 2023), showing that the government-mandated shift to remote work reduced workers' productivity for a large IT company in India. However, we complement existing studies by showing evidence of the impact of WFH on an entire economy, in a setting where firms can choose whether to adopt or not WFH based on their access to high-speed broadband internet. Beyond the pandemic, we find that Italian firms did not experience any negative effects on their productivity. This null effect may reflect the improved ability of firms to integrate remote work effectively, aided by greater familiarity with WFH practices and the use of new digital technologies since the onset of the pandemic.[5]

A second contribution to the literature is to argue that the effects of WFH are heterogeneous across firms. Given the unanticipated nature of the pandemic shock, firms' responses to the pandemic are likely to be even more pronounced (Calvino, Criscuolo, & Ughi, 2024; Crescenzi, Dottori, & Rigo, 2025; Riom & Valero, 2020). While some firms were 'ready', equipped with the necessary organisational flexibility and complementary assets to efficiently integrate remote work practices, others were not. Moreover, small and

[4]The Italian territory is currently divided into 610 travel-to-work areas based on commuting patterns information from the 2011 population census.

[5]The literature has shown that the pandemic primarily redirected technological progress toward supporting remote work (Arntz et al., 2024; Barrero, Bloom, & Davis, 2021; Gathmann et al., 2024).

medium-sized enterprises (SMEs), which represent more than half of the aggregate employment and gross output in most modern economies (Kalemlİ-Özcan et al., 2024), might have been less prepared to take advantage of WFH. Our analysis investigates the differential impact of WFH among Italian firms, comparing firms with a higher versus a lower mix of manual and office workers, more and less digitalised firms, and across firm size categories.

First, our findings highlight that firms predominantly composed of office workers managed to avoid disruptions associated with WFH adoption during the pandemic. In line with this evidence, we find a null effect for firms operating in knowledge-intensive industries. In contrast, the adverse impacts were primarily concentrated in firms with a higher mix of remote and in-person workers (e.g. manufacturing firms). A key implication of this finding is that the impact of WFH on firm productivity goes beyond the sum of individual workers' effects, highlighting the importance of taking into account for negative spillovers between remote and in-person workers (e.g. across companies' functional areas). This evidence is consistent with previous studies showing that the negative impact of the shift to WFH during the COVID-19 pandemic is primarily due to increased coordination and communication costs among employees (Gibbs, Mengel, & Siemroth, 2023; Yang et al., 2022).

Second, we test whether the adoption of remote working practices requires complementary investments in information and communication technologies (ICTs) to work efficiently. Introducing remote working may have been easier for firms that were more digitalised before the pandemic, as they already possessed the complementary technologies and skills necessary for its adoption. In line with our hypothesis, we find that firms that had made significant investments in laptops and server setups before the pandemic had better performance when adopting WFH in 2020.[6]

[6] During the pandemic outbreak, companies primarily used servers to enable remote work by hosting and providing access to essential business applications, data, and communication tools, ensuring business continuity and employee collaboration.

Lastly, we find that larger firms were less negatively affected by the shift to WFH. Given that firm size is a well-established proxy for organisational and managerial capabilities (Bloom, Sadun, & Van Reenen, 2010), this finding suggests that firms with more structured organisations were better positioned to capitalise on remote working.

Beyond the pandemic period, we find no significant long-term heterogeneous effects of WFH adoption across firms, suggesting that initial differences in adaptation largely dissipated over time. The only exceptions concern larger firms and those with a higher share of highly qualified employees. In particular, firms with a greater proportion of staff holding a master's degree or an MBA experienced significant productivity gains in 2022. These findings indicate that organisational and advanced human capital play a key role in enabling firms to capitalise on the long-term benefits of remote work. Consistent with this interpretation, previous research shows that structured managerial practices, such as task standardisation and participatory planning, are positively associated with WFH adoption (Flassak et al., 2023). Moreover, survey evidence suggests that employees began to value managerial roles more highly while working remotely (Krishnamoorthy, 2022).

Our findings remain robust when controlling for the non-random exposure of firms to fibre technology.[7] More urbanised areas are not only more likely to be served by fibre - primarily for cost-minimisation reasons - but are also more central to Italy's economic geography. For example, these areas may have been more exposed to the COVID-19 virus due to their higher population density. As a result, although the local availability of fibre can be considered as good as random, a firm's exposure to non-random shocks, related to its location, may introduce omitted variable bias and undermine the validity of our instrumental variable approach. To address this concern, we follow Borusyak and Hull, 2023 by

[7] The deployment of fibre depended on the location of the national optical packet backbone nodes (*hereafter* nodes). These nodes are upgraded facilities of the old telephone communication network, originally constructed around the early 2000s. The fibre deployment strategy prioritised areas closer to these nodes to maximize coverage efficiency and reduce the initial investment in new infrastructure. This proximity-based deployment leveraged existing node locations to accelerate the rollout of broadband services. As a result, highly densely populated places received the fibre first because the fibre was rolled out in locations closer to these nodes (Boeri, 2023).

incorporating a measure of the expected probability of being served by fibre technology. Including this measure in our baseline specification accounts for the omitted variable bias and, conditional on fixed effects, allows us to identify the causal effect of WFH adoption on firm performance. Our analysis show that both estimation strategies yield very similar results, suggesting that our granular set of fixed effects (defined at the travel-to-work-area level) already captures much of the non-random exposure of firms to these non-random shocks.

The conclusions of this study matter for businesses and policy. First, our study contributes to the ongoing debate on return-to-office mandates. We show that, on average, firms were able to integrate WFH into their operations beyond the pandemic without experiencing productivity losses. Second, we show that complementary investments in ICTs and human capital were critical in enabling firms to adapt successfully and benefit from remote working arrangements. Consequently, the abrupt global shift to WFH induced by the COVID-19 pandemic may have widened pre-existing disparities between larger, better-managed and more digitalised firms and the rest of the business population. These diverging patterns might reinforce large firms' market position and lead to winner-takes-most dynamics due to scalability and the high fixed costs of intangible investments (Andrews, Criscuolo, & Gal, 2016; De Ridder, 2024). Slow diffusion of technology and knowledge can have economy-wide consequences (Berlingieri et al., 2024), slowing productivity growth and increasing market concentration (Akcigit & Ates, 2021, 2023).

Related literature. Our findings contribute to a recent and growing body of research exploring the impact of WFH on firm productivity. On one hand, relying on randomised control trials, Bloom, Han, and Liang (2022), Bloom et al. (2015), and Choudhury et al. (2022) find a positive effect of WFH on workers' and firms' productivity. On the other hand, evidence from firms shifting to WFH during the COVID-19 pandemic shows negative effects (Bao et al., 2022; Emanuel & Harrington, 2024; Gibbs, Mengel, & Siemroth, 2023; Yang et al., 2022), with WFH increasing coordination and communication costs among employees (Gibbs, Mengel, & Siemroth, 2021). Regarding the long-run impact of WFH, Aksoy et al. (2025) find large productivity gains among employees after a firm-wide move to fully remote work in Turkey. Basso, Dottori, and Formai (2024) also show that WFH has uneven effects across firms. While, previous studies have focused on a single or few companies, we provide causal evidence on the adoption of WFH for the quasi-universe of firms in an entire economy. Our analysis is also the first to shed light on the long-term impact of WFH on firm productivity in a developed country setting.

Our instrumental variable approach contributes to a recent body of literature that exploits the availability of broadband internet to estimate its causal effect on firms' performance. While previous studies examined the impact of Asymmetric Digital Subscriber Line (ADSL) technology on firms' size and productivity (Canzian, Poy, & Schüller, 2019; De Stefano, Kneller, Timmis, et al., 2014; DeStefano, Kneller, & Timmis, 2018) or trade (Kneller & Timmis, 2016; Malgouyres, Mayer, & Mazet-Sonilhac, 2021), our analysis relies on the diffusion of fibre technology. To the best of our knowledge, DeStefano, Kneller, and Timmis (2023) and Cambini, Grinza, and Sabatino (2023) are the only other studies using the availability of fibre as an instrumental variable. DeStefano, Kneller, and Timmis (2023) leverage the cross-sectional firms' distance from the exchange and over-time variation in fibre roll-out to study the impact of cloud computing on a sample of UK firms. Cambini, Grinza, and Sabatino (2023) use the deployment of fibre in Italy to explore its impact on firms' performance and productivity. However, our study focuses on the relevance of high-speed internet connection in the adoption of WFH practices.[8] We also contribute to this literature by providing a novel solution to the non-randomness of broadband roll-out to the economic geography of a country. Following Borusyak and Hull (2023), our approach considers the geography of Italy, giving us a control variable for the non-randomness of the availability of fibre technology that is based on a more realistic

[8] In Section 3.2, we explain in detail the importance of fibre technology for effectively implementing remote working practices.

counterfactual topography.

Our paper is also related to a recent body of pandemic-related research studying the role of digital practices and technologies more generally on firms' resilience to the COVID-19 crisis. By relying on ex-ante measures of WFH feasibility, Bai et al. (2021) and Papanikolaou and Schmidt (2022) find that firms with high pre-pandemic WFH potential were more resilient during the crisis. Moreover, recent papers highlight the impact of managerial practices (Lamorgese et al., 2024), technological sophistication (Comin et al., 2022), digital capabilities (Cariolle & Léon, 2022; Oikonomou, Pierri, & Timmer, 2023) and digital infrastructure (Doerr et al., 2021) to mitigate the effects of the pandemic on businesses. Our study is the first contribution providing causal evidence on the effects of WFH on firms' performance and productivity in response to the COVID-19 pandemic.

The rest of the paper is organised as follows. Section 2 presents the data used in our empirical analysis and summary statistics. Section 3 introduces our empirical design, and Section 4 provides evidence on the short- and long-term impact of WFH on firm productivity. Section 5 presents heterogeneous results across different groups of firms, highlighting key mechanisms at play behind the relationship between WFH adoption and firm productivity. Section 6 concludes.

2 Data

To study the impact of WFH on firm productivity, we built a unique data infrastructure. This section outlines the main data sources used in our analysis. We have integrated various types of data, including administrative declarations on the adoption of WFH, balance sheet information from Moody's Orbis and web-scraped data on broadband internet availability. Additionally, we purchased proprietary data on firms' adoption of ICTs from Spiceworks, e-commerce activities from BuiltWith, and information regarding employees' educational level from Revelio Labs.

WFH data. To identify firms that adopt WFH, we use administrative records from the Italian Ministry of Labour and Social Policies. In Italy, employers must report workers who are contractually authorised to work fully or partially from home to guarantee their insurance coverage with INAIL (the National Institute for Insurance against Accidents at Work). INAIL insurance is mandatory by law; employers pay an annual insurance premium to INAIL, and declarations of remote workers have been compulsory since 2017.[9] Our data includes 134 thousands firms and 3.2 million employees that have been at least for a period in WFH since the pandemic.

The data include the firm's tax identifier; workers' details (date of birth, municipality or foreign country of birth, gender); the start and end dates of remote-work spells; and occupation coded using INAIL's four-digit classification. Using these records, we identify, for each worker, the days spent working remotely. Specifically, we compute firm-level measures of WFH adoption such as: (i) an indicator for whether a firm has at least one employee working remotely; and (ii) the number of employees working remotely (both headcount and full-time equivalent) in each year. We provide summary statistics and a validation of our data in Appendix Section D.1.

Firm-level data. Using firms' unique tax identifiers, we merge the WFH data with firm-level financial and geographical information from Moody's (formerly Bureau van Dijk's) historical Orbis dataset. Orbis is based on the Italian government's business register and provides firm-level balance sheet information for both private and publicly listed companies at yearly frequency. Kalemlİ-Özcan et al. (2024) and Bajgar et al. (2020) show that, for Italy, the historical Orbis data are of high quality: the sample covers roughly 90% of total economic activity and displays a size distribution consistent with that of the official Eurostat Structural Business Statistics, which is regarded as the most comprehensive description of business activity for EU countries.[10]

[9] Under the *lavoro agile* framework introduced by Law 81/2017; see this link for further details.

[10] These validation exercises were conducted up to 2015. However, the coverage of Orbis has continued to expand in more recent years, which are those used in our analysis.

In terms of data cleaning, we adopt the following modifications to the original data. First, we exclude companies that consist solely of a single employee to maintain focus on an employment framework where firms offer designated office spaces for their staff. Second, we drop firms that appear more than once in the dataset (as done in Bajgar et al. (2020)) by keeping companies' unconsolidated accounts. This is because sometimes multiple financial accounts are available for the same firm in a given year (e.g. when a firm appears with both a consolidated and unconsolidated account). Lastly, we exclude sectors where the feasibility for remote work is limited and Orbis has a low coverage, such as A (Agriculture, forestry and fishing) and B (Mining and quarrying), and industries from O to U, where the role of the public sector is high. A detailed description of the data and our cleaning procedure is available in Section D.2 in the Appendix.

Broadband data. Data on broadband coverage for the 2015-2021 period are web-scraped from Infratel Italia, a state company in charge of the implementation and monitoring of Italy's Ultra-Broadband Plan. Since 2015, once a year all internet providers are requested to provide information on the availability of broadband telecommunication infrastructures and on the private investment plans for the following three years. The data are collected at the address (house number) level and aggregated to the 2011 census-tract level (*Sezione di Censimento*).[11] We link these data to official geocoded census-tract boundaries, which allows matching with other firm-level datasets using firms' geolocation (latitude and longitude). Infratel reports the share of buildings with access to fibre-to-the-cabinet (FTTC) and fibre-to-the-home (FTTH) technologies, ensuring, respectively, a minimum of 30mbps and 100mbps internet speed. Coverage denotes advertised availability (not realised speeds and not take-up), and we rely on observed coverage rather than operators' forward plans. For summary statistics, see Appendix Section D.3.

[11] The census tract is the smallest statistical unit used in the decennial census.

ICT data. We use data on ICTs from the Aberdeen Computer Intelligence Database (CiTDB), previously known in the literature as the Harte Hanks Database, provided by Spiceworks Ziff Davis Aberdeen Group. This is one of the best sources of ICT data available for Italy, providing detailed information on heterogeneous ICT capital (PCs and laptops), IT infrastructure (servers and data storage) as well as various forms of software like business management systems. This database is constructed through a combination of survey-based interviews and web-scraping techniques. The database has been extensively used for the analysis of the role of ICT, including the seminal work by Bloom, Sadun, and Reenen, 2012 to study the relationship between management practices, ICT and productivity for the US and European countries, DeStefano, Kneller, and Timmis, 2018 to study the effects of ICT on firm performance in the UK, and more recently by Oikonomou, Pierri, and Timmer, 2023 and Calvino, Criscuolo, and Ughi, 2024 to examine the impact of the COVID-19 pandemic on labour markets and the adoption of new technologies. For more details on the merging with the other data sources, see Appendix Section D.4.

E-commerce data. Information on firms' e-commerce activities comes from BuiltWith. The BuiltWith data cover a near-universe of websites (roughly 550 million) and have been collected consistently since 2018. For our purposes, they provide high-frequency snapshots of website technology adoption, which we use to track firms' e-commerce activity around the pandemic shock. We match firms to domains using their registered corporate websites. Following Ragoussis and Timmis (2023), we construct a proxy for e-commerce activity that equals one if the firm's website either supports online sales (e.g., shopping-cart indicators) or implements an online payment technology. This proxy captures the presence of relevant e-commerce technologies, not realised sales or transaction volumes. For details on coverage, see Appendix Section D.5.

Human capital. We use data from Revelio Labs, which gathers information from public LinkedIn profiles. LinkedIn, launched in 2003, is a widely used online platform for professional networking with over 700 million users worldwide. On LinkedIn, users create profiles that list their educational and employment histories, including the universities they attended, their fields and degrees, their employers, job titles and the dates they held these positions. For Italy, Revelio Labs provides access to public information from over 15 million LinkedIn accounts linked to more than 2 million companies as of early 2024.

For our purposes, we identify individuals holding a Master in Business Administration (MBA), a Master's degree, or a Bachelor's degree based on the degree information reported in their LinkedIn profiles. These individual-level data are then linked to our firm-level dataset through a fuzzy matching procedure that uses companies' names, URLs and locations. Further details on the data coverage, cleaning and linking methodology are provided in Section D.6.

Summary statistics. In Table A.1, we present basic summary statistics for the variables included in our empirical analysis for the 2019-2020 period. As expected, the average Italian firm was negatively affected by the crisis, experiencing negative sales and productivity growth rates. Table A.1 also shows that, considering only firms in *essential* industries, 18% of firms switched to remote working in 2020, and (on average) these firms let 10% of their workforce work at home in 2020.

Summary statistics for the 2019–2022 period are reported in Table A.2. In our sample, only 8% of firms adopted remote work in 2022, yet these firms accounted for 30% of total employment and 40% of value added. This suggests that, while WFH adopters represent a small share of the Italian business population, they contribute disproportionately to overall economic activity. On average, firms adopting WFH had 4% of their workforce working remotely at least part of the time in 2022, indicating that most firms operated under mixed arrangements combining hybrid and in-person work.

3 Empirical Design

In this section, we describe the empirical strategy adopted to estimate the causal effects of the pandemic-induced adoption of WFH on firm-level outcomes. The shift to WFH is not random, but rather driven by firms' organisational capabilities and degree of digitalisation that may correlate with firms' productivity. To deal with this endogeneity concern, we instrument WFH adoption with the local availability of fibre technology. Another empirical challenge arises from the non-random roll-out of the fibre network. The deployment of the fibre in space may be determined by the factors (e.g., population density) that may correlate with the spread and severity of the COVID-19 pandemic and other local factors that could affect our firm-level outcomes of interest. Our solution is to control for the presence of this non-randomness in our instrument by recentering our baseline specification around plausibly exogenous variation in access to fibre technology.

3.1 First-Difference Framework

Using a first-difference framework, we document firms' performance before and after the start of the COVID-19 pandemic by comparing firms' using or not flexible work arrangements. Our baseline model is defined as follows:

$$\Delta log(Y_i) = \alpha + \beta WFH_i + \theta X_i^{2019} + \gamma_j \times \gamma_p + \varepsilon_i; \tag{1}$$

where $\Delta log(Y_i)$ indicates the difference in (log) sales, labour productivity (as value added per employee) or total factor productivity (TFP) between the years 2020, 2021 or 2022 and 2019.[12] WFH_i is a binary variable that equals one when firm i has at least one employee in remote work in that year. Our coefficient of interest is β which is identified by comparing firms that started using WFH and firms that did not adopt WFH.

[12] TFP provides a commonly used indicator for the overall productive performance of a company (DeStefano, Kneller, & Timmis, 2018) and it is calculated using the methodology developed in Wooldridge (2009) using information on value added, cost of materials and total assets to define the production function.

To improve the comparability between the treatment and control groups, we exclude firms using WFH before the pandemic (accounting for less than 1% of the sample). To control for a wide range of unobservables affecting firms' performance (e.g. the differential severity of the lockdown imposed by the Italian government or the spread of the virus in the working population), we also include travel-to-work-areas (γ_p) interacted with 4-digit industry fixed-effects (γ_j).[13] Lastly, X_i is a vector of firm controls, measured in 2019, including a measure for firms' size (log of the number of employees), the firm's age and labour productivity (log of value added per employee).

In the short-term analysis (comparing firms' performance in 2020 with that in 2019), we exclude companies in *non-essential* industries, as these firms were not permitted to operate in person during the initial lockdown (from March to May 2020) and could only operate remotely. Consequently, the firms considered in this analysis were classified as *essential* by the Italian government and therefore could independently decide whether to implement remote working practices in 2020. This changes the interpretation of β, which is evaluated in a setting where firms can choose whether or not to adopt WFH, and were not constrained by governmental restrictions. Firms operating in essential industries, and thus included in the short-term analysis, account for roughly 40% of observations and 50% of employment in 2019.

By contrast, our long-term analysis, examining changes in firm performance in 2021 and 2022 relative to 2019, includes all firms in the Italian economy. However, to avoid firms moving from the treatment group to the control group, we exclude those that stopped using WFH in 2021 or 2022. The long-term analysis also considers a balanced panel of firms, including only those operating continuously between 2019 and 2022.

Lastly, to study whether the role played by WFH in firm productivity is heterogeneous across firms, we include in equation 1 an interaction term between WFH_i and Z_i. This

[13] This is the same detail of classification that was used to define the essential industries allowed to operate during the lockdown in 2020. A list of essential industries is available at this link.

results in the following specification:

$$\Delta log(Y_i) = \alpha + \beta_1 WFH_i + \beta_2 Z_i + \beta_3 WFH_i \times Z_i + \theta X_i^{2019} + \gamma_j \times \gamma_p + \varepsilon_i; \qquad (2)$$

where Z_i denotes one of the following variables: $Size_i^{h,l}$ that equals 1 when firm i has fewer than h employees and at least l employees; ICT_i indicating the number of laptops or servers per employee; and $Postgrad_i$, denoting the share of employees with postgraduate qualifications (a master's degree or an MBA). Section 5 shows the results of estimating this equation where our measure of WFH adoption and the interaction term with Z_i are instrumented by the local availability of fast broadband internet and its interaction with Z_i.

3.2 Instrumental Variable

We are interested in the causal impact of the pandemic-induced adoption of WFH on Italian firms' performance and productivity. However, the literature on technology adoption has highlighted that the choice to adopt WFH practices could be correlated with unobservable characteristics of the firm. As a result, the quality of management could have caused at the same time the adoption of WFH and the firms' growth during the COVID-19 crisis. To overcome this endogeneity concern in our estimation, we instrument our main explanatory variable with the local availability of high-speed fibre broadband in the year 2019.[14]

IV relevance. Italy underwent a significant upgrade in broadband technology starting in 2015. In 2014, nearly all Italian municipalities had ADSL coverage but lacked fibre access; by 2019, however, fibre reached 85% of the population (Boeri, 2023). Unlike ADSL,

[14] Although we do not find plausible that any firm had the opportunity to capture the central Government and speed up the rollout of broadband in a certain area in the immediate aftermath of the COVID-19 outbreak, we still use the pre-treatment infrastructure to address any endogeneity concern. Moreover, between 2019 and 2020, due to the disruption caused by the pandemic, only 1.2% of Census tracts recorded a relevant increase in broadband coverage. We exclude the 3,686 firms located in these territories.

which operates over copper cables, fibre offers higher suitability for remote work due to its symmetrical upload and download speeds. This is essential for remote work activities, such as video conferencing, large file transfers, and other real-time applications, which are usually centralised at the firm's main location. Moreover, fibre supports multiple simultaneous connections without major performance degradation, whereas ADSL faces constraints in handling multiple devices effectively. Lastly, while ADSL typically offers download speeds in the range of 1 Mbps to 7 Mbps, fibre guarantees at least 30 Mbps for both downloads and uploads.[15]

Table A.3 indicates that the local availability of fibre broadband is a strong predictor of firms' WFH adoption during the pandemic. Column 1 shows a positive and strong relationship between our instrument (the local availability of FTTC) and the adoption of WFH in 2020, reassuring us about the relevance of our instrument. Column 2 also includes the availability of FTTH, which provides at least 100 Mbps of download and upload capability and should further improve the capacity of firms to operate WFH-related technologies. The results confirm that firms with access to FTTH had an even greater probability of adopting WFH in 2020. Note that the coefficient of $Fibre(FTTH)$ is equivalent to an interaction term with $Fibre(FTTC)$, as in our empirical framework, firms with access to FTTH also mechanically have access to FTTN. Thus, the coefficient of $Fibre(FTTH)$ captures the additional effect of having access to FTTH. This evidence implies that WFH adoption is positively related to the instrument, at both low and high values, reassuring us on the monotonicity of this relationship. Moreover, pre-pandemic FTTC availability remains a significant predictor of WFH adoption beyond the pandemic, both in 2021 and 2022 (Table A.4).[16]

[15] A potential alternative instrument considers that workers may also be negatively affected by the lack of fast broadband internet connection. Due to data limitations, we do not know where the workers reside and are therefore unable to construct a measure of fibre availability at the worker level. However, since we are comparing companies within local labour markets, as long as the distribution of workers in space is similar between companies served by fibre or not, the companies' workforce should have homogeneous internet coverage, and this should not bias our estimates. Moreover, while a worker could potentially work remotely using wireless technology, this would be impractical for a company.

[16] Throughout the paper, the term fibre refers to FTTC connections unless otherwise specified.

IV validity. In this paragraph, we provide evidence supporting the claim that the fibre availability is good as random since it was rollout progressively in adjacent territories to minimise public spending in a relatively short time period. First, as shown in Figure B.3, the probability of being served by fibre technology quickly decays with distance, with areas more than 6 km away (from areas already covered) with close to zero probability of being served by fibre in the future. Second, a simple correlation analysis (Table A.5) reveals that economic factors, such as the growth in labour productivity, wages, employment and the share of large firms, are not statistically related to the probability of being served by high-speed broadband internet in the future. In contrast, distance matters, with areas closer to existing fibre technology being more likely to be covered by the fibre infrastructure in the coming year.

Third, to rule out even further that the broadband roll-out was not driven by economic factors, we examine whether firms covered by fibre technology may be different from firms not covered by high-speed internet (in 2019). Figure B.4 shows that firms located in areas with access to a slower internet connection have similar characteristics than firms located in areas with access to fibre broadband. Lastly, to test whether the broadband roll-out was targeted at areas where firms were expected to grow quickly in the future, we examine whether the timing of the access to the fibre infrastructure is related to firm performance. Figure B.5 shows the absence of pre-trends in sales, labour productivity and TFP in the years before treatment. This event study regression is estimated relying on the estimator developed by Callaway and Sant'Anna (2021).

Exclusion restriction. Another concern is that access to a fast broadband internet connection may affect firm productivity through channels other than the adoption of WFH (Akerman, Gaarder, & Mogstad, 2015; DeStefano, Kneller, & Timmis, 2018). To test whether we are picking up the effect of a broader technological change, we examine whether the instrument is related to alternative types of fibre-enabled technologies that may have helped firms during the crisis.

First, firms with access to high-speed broadband internet may have been able to more efficiently switch to e-commerce sales during the lockdown periods. Even though Italian firms do not rely intensively on e-commerce, as shown by Figure B.6, it could be possible that online sales allowed Italian firms to adapt and respond effectively to the challenges imposed by the pandemic. We test the relationship between the local availability of fibre technology and firms' shift to online sales by examining the adoption of online payment methods and online e-commerce technologies on their websites. Table A.6 indicates that access to fibre technology is not significantly related to any of these measures. One possible explanation is that managing a website imposes lower broadband requirements on firms compared to adopting WFH.

Second, while the pandemic prompted firms to introduce a wide range of broadband-intensive applications, the large majority were linked to the adoption of WFH, including cloud computing, collaboration software, laptops, and IT security tools (Calvino, Criscuolo, & Ughi, 2024). As a result, the estimated treatment effect captures the impact of WFH together with the complementary digital technologies it triggers. Lastly, although fibre could, at least in principle, enhance productivity through applications unrelated to remote work, these new technologies could have helped firms navigate the pandemic, thereby improving performance and resilience. This, however, would bias our short-term estimates downwards, leading to an underestimated effect.

3.3 Controlling for non-random exposure

The rollout of fibre broadband infrastructure in Italy was governed by the old telephonic network line. Fibre was introduced sequentially, starting from a set of 35 central nodes located predominantly in urban areas (as shown in Figure B.1). Consequently, areas closer to these nodes were served first for engineering reasons. Figure B.2 shows this pattern for the Veneto region (in the North-East of Italy), where areas in proximity to major cities such as Padova, Venice, and Verona exhibit significantly higher fibre coverage by 2019.

This spatial pattern implies that even if fibre availability were randomly assigned throughout the network, exposure to fibre would remain correlated with underlying geographic characteristics, such as urbanisation and economic geography. As a result, fibre-enabled areas may systematically differ from peripheral ones in ways that correlate with both treatment take-up and firm-level outcomes. In particular, if more urban locations were disproportionately affected by COVID-19 disruptions (due to higher population density), then proximity to fibre nodes may mechanically correlate with more severe shocks. Thus, firms in such areas may be more likely both to adopt WFH and to experience pandemic-related downturns. This tendency can bias our estimates.

In the context of this study, the use of TTWA fixed effects are likely to absorb the main spatial confounders, thereby mitigating concerns about omitted variable bias. Nevertheless, to further address endogeneity concerns, we control for the non-random exposure to fibre technology by introducing a novel measure of the expected access to fibre. We construct this measure based on the insights of Borusyak and Hull (2023), by deriving a counterfactual fibre network modelled as a function of the geographical and institutional characteristics of Italy. The rationale is as follows: the likelihood of a census tract receiving a fibre connection depends on its proximity to the nearest node (for cost-minimizing reasons) and the node's capacity to deliver the fibre (*hearafter* referred to as decay). The node's decay may be influenced by the topography of an area (delivering fibre in mountainous areas can be challenging) and its institutional characteristics (some areas are more efficient in delivering public infrastructure). We construct our counterfactual fibre network by permuting our measure of decay across nodes, while maintaining the geographical node-census tract distance and the overall dimension of the fibre network (the total number of census tracts covered by fibre in 2019) constant.

By design, our measure of expected access to fibre should approximate a census tract's exposure to high-speed broadband connection. Table A.7 confirms that our counterfactual fibre network is a strong predictor of the actual fibre availability. In our analysis, we therefore follow Borusyak and Hull (2023) by including our counterfactual fibre variable as a control in our specification. This should recentre the impact of actual fibre availability, providing us with the unbiased effect on our firm-level outcomes of interest.

Modelling expected fibre network. We assume that the probability of receiving fibre technology is a function of i) the distance between the census tract i and the node j ($DistanceNode$); and ii) the node's ability to deploy fibre effectively over space ($\hat{\alpha}$) that is estimated as the fixed effects (α_j) in the following specification:

$$P(Fibre_i) = \beta DistanceNode_{ij} + \alpha_j + \varepsilon_i. \tag{3}$$

Where $Fibre_i$ equals one if the census tract i is served by fibre in 2019. Equation 3 allows to retrieve two parameters used to construct our counterfactual measure: $\hat{\beta}$ and $\hat{\alpha}_j$. We then model the expected access to fibre with a logistic function as follows:

$$P(\widehat{Fibre_i}) = \frac{1}{1 + \exp(\hat{\beta} \cdot DistanceNode_{ij} - \hat{\alpha}_j)}; \tag{4}$$

where $DistanceNode_{ij}$ is the log distance between census tract i and its closest node j and $\hat{\alpha}_j$ is node j capacity to deploy the fibre. By subtracting $\hat{\alpha}_j$ from $DistanceNode_{ij}$, we are effectively capturing the trade-off between the negative impact of distance and the positive impact of $\hat{\alpha}_j$. Intuitively, the further the distance, the lower the probability of fibre coverage; and the lower the decay, the stronger the node's coverage capability, and this should increase the probability of fibre coverage.

4 Results

In this section, we examine the relationship between WFH and firm productivity. First, we estimate the naïve short-term effect of WFH adoption on firms' growth in sales, value added, and productivity. Second, we instrument WFH using firm-specific access to broadband fibre technology. Third, we replicate our analysis using different cuts of the data to verify the robustness of our findings. Fourth, we present evidence on the longer-term effects of WFH.

Short-term OLS results. Table 1 shows that firms starting to use remote working as a result of the lockdown measures imposed in 2020 performed better than firms that didn't adopt WFH. The coefficient in column (1) indicates that firms adopting WFH in 2020 recorded 5.4% higher growth in sales than companies not adopting remote working. We also examine the intensive margin of WFH adoption during the crisis, measured as the firm's share of workers in WFH in 2020 (in the total number of employees). Table D.1 shows that firms with a larger share of workers in WFH experienced larger growth in sales and productivity during the pandemic. These findings may be however driven by firms' unobserved characteristics: better-managed firms were better able to shift to WFH arrangements and at the same time more prepared to face the pandemic crisis. As a result, the OLS estimates are likely to overstate the true impact of WFH (i.e. upward bias).

Table 1: Short-term OLS results

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (dummy)	0.0539***	0.0492***	0.0470***
	(0.00334)	(0.00415)	(0.00369)
Observations	104,446	104,446	104,446
R-squared	0.259	0.236	0.230
Firm-level controls	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log labour productivity in column 2 and log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Short-term IV results. Table 2 presents the results instrumenting the adoption of WFH in 2020 with a dummy indicating whether firms have access to fibre technology in 2019. The instrument seems a good predictor of the treatment. The F-test is well above the conventional value of 10, meaning that we can safely exclude weak instrument concerns. Columns (1) to (3) show the second-stage estimates. The coefficients represent the average percentage variation over the post-treatment period for firms adopting WFH, relative to the pre-treatment period and to firms not using WFH. We find a negative and large impact of WFH on firms' labour productivity and TFP, but not significant for sales. This latter evidence suggests that our specification is able to control for any change in demand that could affect firms' sales during the pandemic.

The coefficient in column (3) indicates that firms adopting WFH during the COVID-19 pandemic experienced a reduction of 37% of their TFP. This growth rate appears large, however the summary statistics in Table A.1 show that the mean firm has a TFP growth rate of -15% in 2020. Moreover, Gibbs, Mengel, and Siemroth, 2023 found for a large IT company in India that the government-mandated shift from in-person to remote work led to a 20% reduction in workers' productivity. Our larger estimates can be reconciled with the fact that, as shown in Section 5, the mix between in-person and remote workers, accounted in our analysis, matters in amplifying the productivity decline.

Table 2: Short-term IV results

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (dummy)	0.133	-0.340**	-0.370**
	(0.136)	(0.173)	(0.156)
Expected fibre	-0.00754	-0.00657	-0.00415
	(0.00869)	(0.0107)	(0.00984)
Observations	104,446	104,446	104,446
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	56.9	56.9	56.9

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log value added in column 2 and log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Robustness checks. Our findings are robust to alternative specifications and various cuts of the data. First, we test alternative measures of WFH, including the share of employees in WFH (Section C) and the duration in months of WFH adoption (Table A.8). Results remain consistent across these measures. Second, to minimise the role played by unobserved factors in driving our results, we augment our set of fixed effects by comparing firms within TTWAs and by area type (residential, industrial, rural or mountainous). As shown in Table A.9, the coefficients are qualitatively unchanged.

Third, we account for the severity of the pandemic by excluding firms that exited the market in 2021 or 2022. Results in Table A.10 confirm the robustness of our findings. Fourth, we exclude large firms (with over 250 employees) and as shown in Table A.11, results remain unchanged. This latter robustness controls for the fact that a few very large firms might have dedicated access to a high-speed broadband internet connection, or might have influenced the deployment of the fibre by the government. Lastly, we exclude firms that changed their location during the pre-pandemic period (2015–2019), as these firms may have relocated to gain access to fibre. As shown in Table A.12, our conclusions remain unaffected. While we cannot entirely rule out this channel, we believe it is unlikely to pose a concern for our analysis. First, we observe that most relocations (in the 2015-2019 period) occurred across TTWAs, meaning our fixed effects should account for these patterns, as we compare firms within the same TTWA. Second, given that the fibre rollout lasted only four years and aimed to cover the entire Italian population, even if firms had anticipated the deployment, the high costs associated with relocation make it unlikely that they would have moved for this reason.

Long-term IV results. To estimate the long-term impact of WFH on firm performance and productivity, we consider the full sample of firms that adopted WFH in the 2020-2022 period, comparing their productivity with that of firms that did not implement remote work practices in the same year. This allows us to test whether firms adopting WFH post-pandemic exhibit different growth trajectories compared to non-adopters. Tables 3 show that while the coefficient for TFP is negative and statistically significant in 2020, both its magnitude and significance decrease in 2021 and 2022. These results suggest that WFH adoption, on average, does not negatively affect firm productivity beyond the pandemic.

This finding remains consistent when looking at labour productivity growth (Table A.13), when excluding large firms (with over 250 employees) and those that relocated in the pre-pandemic years (2015–2019), and is also robust to a more granular set of fixed effects that account for variation within TTWAs, detailed industry classifications, and area types (Tables A.14-A.16). Lastly, the results are qualitatively and quantitatively unchanged when excluding firm adopting WFH in 2021 and 2022 (Table A.17). In this latter analysis, we focus on firms that adopted WFH in 2020 and continued its use through 2021 and 2022, suggesting that pandemic WFH adopters were eventually able to adapt and mitigate any initial disruptions associated with remote work.

Table 3: Long-term results: TFP

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (dummy)	-0.905**	-0.578	-0.531
	(0.422)	(0.437)	(0.431)
Expected fibre	0.00486	0.00256	0.00433
	(0.00770)	(0.00759)	(0.00817)
Observations	178,930	178,930	178,930
Firm-level controls	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	21.9	16.7	16.6

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5 Heterogeneous Effects

Our baseline results indicate that during the COVID-19 pandemic, Italian firms adopted WFH practices despite encountering adverse disruptions, including reduced growth in labour productivity and TFP. The abruptness of the COVID-19 shock meant many firms were inadequately equipped for the shift, lacking essential ICT infrastructure and digital resources. Additionally, with limited pre-pandemic experience in flexible work arrangements, most firms were unprepared for the complex organisational adjustments necessary for effective remote working, which extend beyond a mere change in work location and (as shown) require time for proper implementation.

In this section, we explore the potential mechanisms underlying the negative relationship between WFH and firm productivity. First, we investigate whether the increased communication and coordination costs from WFH adoption could explain our negative findings. Second, we examine whether pre-pandemic investments in WFH-related ICTs and the presence of highly qualified employees and organisational capital helped mitigate the adverse effects associated with WFH adoption.

Manual versus office workers. Existing literature shows that the pandemic-driven shift to WFH raised communication and coordination costs across workers, affecting their productivity (Emanuel & Harrington, 2024; Gibbs, Mengel, & Siemroth, 2023; Yang et al., 2022). To assess the role of these costs in our findings, we construct a measure of WFH potential at the 4-digit industry level, representing the share of workers who could feasibly work remotely based on task requirements.[17] Our hypothesis is that WFH disproportionately affected firms with lower WFH potential, where in-person and remote work were more mixed.

Table 4 shows a negative effect of WFH adoption on TFP in industries with low WFH potential. This evidence suggests that industries with less than one-third of office-based workers experienced negative impacts from WFH in 2020. This outcome may stem from coordination and communication challenges between remote and on-site workers, especially across firms' functional areas (e.g. production and warehousing versus support services).

A sector-specific analysis supports this conclusion. Columns 2 and 3 report results for the manufacturing sector, which employs about one-third of Italy's workforce, and knowledge-intensive industries, including information and communication, financial and insurance services, and professional activities. Despite relatively low WFH adoption during the pandemic, manufacturing WFH adopters showed lower productivity growth. Conversely, firms in knowledge-intensive sectors showed no significant disruptions. Similar conclusions are reached when looking at the effects on labour productivity (see Table A.18 in the Appendix).

[17] Our measure of WFH potential reflects the proportion of employees able to perform their tasks remotely, derived using the method of Dingel and Neiman (2020), who classify occupations by home-based work suitability for the U.S. based on O*NET data. We aggregate this measure at the 4-digit industry level using employment data from the LFS; further details are provided in Crescenzi, Dottori, and Rigo (2025). High (low) WFH potential indicates that more (fewer) than 33% of employees in an industry could work remotely.

Table 4: Short-term results: TFP & Manual vs office workers

VARIABLES	(1) All firms Δ log(TFP)	(2) Manufacturing Δ log(TFP)	(3) KIS Δ log(TFP)
WFH (dummy) × Low WFH potential	-0.771**		
	(0.355)		
WFH (dummy) × High WFH potential	-0.0456		
	(0.144)		
WFH (dummy)		-0.836**	-0.105
		(0.385)	(0.133)
Observations	104,446	24,818	26,879
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 2-digit industry fixed effects	.	✓	✓
TTWA × 4-digit industry fixed effects	✓	.	.
K-Papp F-stat	8.8	11.7	39.1

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log TFP. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

ICTs. Here we focus our analysis on two key measures of ICT capital complementary to remote work: laptops (as a proxy of IT capital) and servers (as a proxy of IT infrastructure). Tables 5 shows that firms with higher pre-pandemic investments in laptops and setting-up servers had better performance when adopting remote work in 2020. Interestingly, comparing column 1 (all firms) with column 2 (only firms with at least 10 employees) suggests that the presence of laptops is not helpful for micro firms, suggesting the presence of a complementarity between digital investments and firms' organisational capabilities. Our results are confirmed when examining the impact on labour productivity (Table A.19). Overall, these findings highlight the essential role of digital investments in enabling firms to adapt to and fully leverage remote work arrangements.

Table 5: Short-term results: TFP & Investments in ICTs

VARIABLES	(1) All firms Δ log(TFP)	(2) >= 10 employees Δ log(TFP)	(3) All firms Δ log(TFP)
WFH (dummy)	0.00972	-0.00622	0.00500
	(0.146)	(0.148)	(0.162)
Laptops per employee	-0.112	-0.296**	
	(0.127)	(0.138)	
WFH (dummy) × Laptops per employee	0.309	0.558*	
	(0.412)	(0.303)	
Servers per employee			-0.368**
			(0.144)
WFH (dummy) × Servers per employee			0.704**
			(0.298)
Observations	34,643	23,802	34,643
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	11.9	13.8	13.8

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log TFP. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Organisational and human capital. To assess the role of firms' organisational and managerial capabilities in the relationship between WFH and productivity, we perform two analyses. First, we examine whether the presence of highly educated employees (with an university degree) and employees holding an MBA facilitated the transition to remote work and enabled firms to take advantage from its adoption. However, we do not observe any differential effects for firms with a higher share of postgraduate-educated employees (Table A.22).

Second, we use firm size (measured by the pre-pandemic number of employees) as a proxy for the presence of organisational capital. Previous studies suggest a close association between the presence of organisational and knowledge-based assets and firm size (Bloom, Sadun, & Van Reenen, 2010). We implement this analysis by categorising firms into groups based on their number of employees. Tables A.20 and A.21 show that small firms (with less than 10 employees) were the most negatively impacted by WFH adoption, while larger firms were no disrupted by the shift to remote working.

Long-term heterogeneous results. We now move beyond the pandemic period to examine the heterogeneous effects of WFH on Italian firms over the longer term. Table 6 shows that, for a subset of firms, those with a higher share of highly qualified employees, defined as workers holding a master's degree or an MBA, experienced positive effects from WFH adoption in 2022.[18] Moreover, we find that larger firms experienced productivity gains from the adoption of WFH in 2021 and 2022 (Table A.23). These results supports the hypothesis that the presence of highly qualified personnel and stronger organisational capital enhance firms' ability to benefit from remote work.[19]

Finally, we find no evidence that firms' pre-pandemic investments in ICT had a lasting impact beyond the initial transition to remote work. This suggests that firms may have quickly addressed any gaps in complementary digital technologies (Tables A.24–A.25). Similarly, we find no differential long-term effects when splitting the sample by the degree of WFH potential (Table A.26) or when focusing separately on the manufacturing and knowledge-intensive service sectors (Tables A.27 and A.28).

[18] However, the Kleibergen–Paap first-stage F-statistics fall below the conventional weak-instrument threshold of 10, suggesting caution in interpreting these estimates. The low first-stage F-statistic can be partly attributed to the small number of observations available for this subsample, which weakens the statistical power of our IV approach.

[19] These analyses are implemented on the full sample, excluding construction (F) and accommodation & food service activities (I). These industries predominantly require in-person activities, have less scope for remote working arrangements, and limited scope for the adoption of structured managerial practices designed to coordinate dispersed teams.

Table 6: Long-term results: TFP & Employees with postgraduate degrees

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
Postgrad degrees (share)	-0.0578	-0.0575	-0.239***
	(0.0642)	(0.0654)	(0.0857)
WFH (dummy)	-0.108	0.167	-0.231
	(0.273)	(0.276)	(0.336)
WFH (dummy) $\times$ Postgrad degrees (share)	0.408	0.202	0.959**
	(0.350)	(0.356)	(0.411)
Observations	24,177	24,177	24,177
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	5.2	5.7	4.2

Notes: This analysis is based on the full sample of firms, excluding Construction (F) and Accommodation & food service activities (I). The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusions

This paper provides causal evidence on the productivity effects of post-pandemic WFH adoption using previously unexplored administrative data on remote workers. We provide three main contributions to the literature. First, we show for an entire economy that the adoption of remote work practices during the COVID-19 pandemic had, on average, a negative effect on productivity. Second, we extend the analysis beyond the pandemic period to assess the longer-term implications of WFH, finding that firms adopting remote work in 2021 and 2022 did not, on average, experience productivity losses.

Third, we shed light on the channels trough which remote work affects firm performance. The initial negative effect was particularly pronounced among firms employing a higher share of both manual and office workers, suggesting that the observed productivity decline may be attributed to increased communication and coordination costs. In contrast, large firms and those equipped with complementary ICTs were better able to mitigate these negative effects. Moreover, larger and better-managed firms experienced productivity gains from WFH adoption beyond the pandemic. This evidence highlights the critical role of investments in digital technologies and organisational capital in enabling firms to effectively implement remote work.

While our paper provides comprehensive evidence on the short- and long-term effects of remote work on firms, several important questions remain. First, relatively little is known about the potential costs that WFH may pose for innovation and in building up corporate culture, both long-term drivers of firm growth. Second, although we document substantial heterogeneity in the effects of WFH across firms, an important follow-up question concerns how these micro-level effects aggregate, and which types of firms and workers ultimately gain or lose from its adoption.

Our findings also carry policy implications. Given the heterogeneous responses to WFH, we caution against one-size-fits-all approaches to promoting remote work or digital adoption. Untargeted public interventions may fail to generate positive outcomes if firms lack the absorptive capacity or organisational capital required to effectively leverage new digital technologies.

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"Work from home and Firm Productivity: The Role of ICT and Size"

Appendix - For Online Publication Only

A Additional Tables

A.1 Descriptive Statistics

Table A.1: Summary statistics, 2020

Variables	Mean	St. Dev.	Median	Min	10pct	90pct	Max	Obs
Balance Sheet Variables								
Δ log Sales	-0.05	0.34	-0.05	-1.08	-0.43	0.29	1.37	104446
Δ log VA per employee	-0.08	0.42	-0.06	-1.58	-0.55	0.34	1.66	104446
Δ log TFP	-0.15	0.37	-0.12	-1.22	-0.59	0.23	1.2	104446
Age	16	14	13	0	2	35	119	104446
VA per employee (log)	11	1	11	7	10	11	17	104446
WFH Variables								
WFH (dummy)	0.18	0.38	0	0	0	1	1	104446
WFH (share)	0.1	0.27	0	0	0	0.47	1	104446
Digital Variables								
Laptops per employee	0.15	0.14	0.1	0	0.02	0.33	1	44287
Servers per employee	0.05	0.12	0	0	0	0.14	1	44287
Educational Variables								
Postgrad degrees per employee	0.21	0.22	0.17	0	0	0.5	2	16432

Notes: These descriptive statistics are based on the sample of firms operating in *essential* industries in 2020. Δ denotes the 2019-2020 change. The variable in levels are instead taken in the year 2019, including number of employees, age (in years), value added per employee (in log), number of laptops per employee, number of servers per employee, and the share of employees with a Master's or MBA degree.

Table A.2: Summary statistics, 2022

Variables	Mean	St. Dev.	Median	Min	10pct	90pct	Max	Obs
Balance Sheet Variables								
Δ log Sales	0.27	0.47	0.21	-1.37	-0.2	0.83	1.93	178930
Δ log VA per employee	0.17	0.46	0.14	-1.8	-0.33	0.71	1.77	178930
Δ log TFP	-0.04	0.4	-0.04	-1.43	-0.51	0.42	1.2	178930
No of Employees	17	61	7	2	2	30	5281	178930
Age	16	14	13	0	2	36	119	178930
VA per employee (log)	11	1	11	6	10	11	17	178930
WFH Variables								
WFH(dummy)	0.08	0.27	0	0	0	0	1	178930
WFH(share)	0.04	0.17	0	0	0	0	1	178930
Digital Variables								
No Laptops per employee	0.16	0.14	0.13	0	0.02	0.33	1	68417
No Servers per employee	0.05	0.09	0	0	0	0.14	1	68267
Educational Variables								
Postgrad degrees per employee	0.22	0.25	0.16	0	0	0.5	2	35244

Notes: These descriptive statistics are based on the whole sample of firms in 2022. Δ denotes the 2019-2022 change. The variable in levels are instead taken in the year 2019, including number of employees, age (in years), value added per employee (in log), number of laptops per employee, number of servers per employee, and the share of employees with a Master's or MBA degree.

A.2 IV validity & relevance

Table A.3: First-stage results

VARIABLES	(1) Extensive WFH (dummy)	(2) Extensive WFH (dummy)	(3) Intensive WFH (share)	(4) Intensive WFH (share)
Fibre (FTTC)	0.0261***	0.0192***	0.0154***	0.00968***
	(0.00346)	(0.00358)	(0.00207)	(0.00211)
Fibre (FTTH)		0.0171***		0.0141***
		(0.00291)		(0.00201)
Observations	104,446	104,446	104,446	104,446
R-squared	0.358	0.359	0.374	0.374
Firm-level controls	✓	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓	✓

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is a dummy indicating whether a firm adopted WFH in 2020 (columns 1 and 2) and the share of employees adopting WFH in 2020 (columns 3 and 4). All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: First-stage results: 2020-2022

VARIABLES	(1) 2019-2020 WFH (dummy)	(2) 2019-2021 WFH (dummy)	(3) 2019-2022 WFH (dummy)
Fibre	0.00764***	0.00713***	0.00760***
	(0.00163)	(0.00174)	(0.00186)
Observations	178,930	178,930	178,930
R-squared	0.349	0.352	0.364
Firm-level controls	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓

Notes: This analysis is based on the full sample of firms. The dependent variable is a dummy indicating whether a firm adopted WFH in 2020 in column 1, in 2021 in column 2 and in 2022 in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Adjacent roll-out correlations

	(1) Fiber adoption New infrastructure in t	(2) Fiber adoption New infrastructure in t	(3) Fiber adoption New infrastructure in t
log distance from infrastructure (t-1)	-0.0507***	-0.0473***	-0.0462***
	(0.00558)	(0.00369)	(0.00308)
Δlog employment (t-4 - t-1)	-0.00163	-0.00167	-0.00148
	(0.00148)	(0.00145)	(0.00152)
Δlog avg. wage (t-4 - t-1)	0.000758	0.000956	0.00107
	(0.00144)	(0.00119)	(0.00115)
Δlog large firms share (t-4 - t-1)	0.00138	0.000865	0.00184*
	(0.00101)	(0.000975)	(0.00111)
Observations	100,094	100,094	100,094
R-squared	0.058	0.094	0.144
FE	NO	Province	TTWA

Notes: The dependent variable is a dummy that equals 1 if the census tract is covered by fibre technology. All the variables are taken at the census tract level by aggregating information at the firm-level. Standard errors are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Fibre and E-commerce

VARIABLES	(1) WFH (dummy)	(2) Δ E-commerce
Fibre	0.0331***	0.00113
	(0.00438)	(0.00292)
Observations	74,827	74,302
R-squared	0.365	0.169
Firm-level controls	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓

Notes: This analysis is based on the sample of firms operating in essential industries. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Actual and expected fibre

VARIABLES	(1) Fibre	(2) Fibre	(3) Fibre	(4) Fibre
Expected fibre	0.141***	0.179***	0.169***	0.141***
	(0.0244)	(0.0185)	(0.0250)	(0.0357)
Observations	89,250	89,250	89,250	89,246
R-squared	0.022	0.077	0.121	0.249
NUTS-2 fixed effects	.	✓	.	.
NUTS-3 fixed-effects	.	.	✓	.
TTWA fixed effects	.	.	.	✓

Notes: The dependent variable is a dummy that equals 1 if the census tract is covered by fibre technology. All the variables are taken at the census tract level. Standard errors are clustered at the travel-to-work-area level. *** p<0.01, ** p<0.05, * p<0.1.

A.3 Short-term results - Robustness

Table A.8: Short-term results: Duration in months of WFH

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (Number of month)	0.0238	-0.0608*	-0.0662**
	(0.0244)	(0.0314)	(0.0286)
Observations	104,446	104,446	104,446
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	40.1	40.1	40.1

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log value added in column 2 and log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Short-term results: TTWA $\times$ Area $\times$ 4-digit industry FEs

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (dummy)	0.135	-0.298*	-0.375**
	(0.144)	(0.180)	(0.165)
Observations	99,151	99,151	99,151
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ Area type $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	51.3	51.3	51.3

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log labour productivity in column 2 and log TFP in column 3. All specifications include travel-to-work areas $\times$ Area type $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log labour productivity per employee and age). Standard errors are clustered at the travel-to-work area $\times$ Area type $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.10: Short-term results: Exclude firms exiting in 2021 or 2022

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (dummy)	0.0310	-0.477**	-0.448***
	(0.146)	(0.195)	(0.174)
Observations	85,513	85,513	85,513
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 2-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	43.9	43.9	43.9

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log value added in column 2 and log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.11: Short-term results: Exclude large firms (with over 250 employees)

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (dummy)	0.133	-0.318*	-0.352**
	(0.137)	(0.174)	(0.157)
Observations	103,464	103,464	103,464
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	56.3	56.3	56.3

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log value added in column 2 and log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.12: Short-term results: Exclude firms sorting pre-pandemic

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (dummy)	0.0734	-0.330*	-0.303*
	(0.130)	(0.181)	(0.163)
Observations	66,299	66,299	66,299
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	40.3	40.3	40.3

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log value added in column 2 and log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.4 Long-term results: Robustness

Table A.13: Long-term results: Labour productivity

VARIABLES	(1) 2019-2020 Δ log(VA/Empl)	(2) 2019-2021 Δ log(VA/Empl)	(3) 2019-2022 Δ log(VA/Empl)
WFH (dummy)	-1.187**	-0.526	-0.618
	(0.489)	(0.481)	(0.491)
Observations	178,930	178,930	178,930
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	21.9	16.7	16.6

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log labour productivity in column 1, the 2019-2021 change in log labour productivity in column 2 and the 2019-2022 change in log labour productivity in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.14: Long-term results: TFP & Exclude large firms

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (dummy)	-0.945**	-0.591	-0.515
	(0.458)	(0.468)	(0.464)
Observations	177,752	177,752	177,752
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	19.5	15.1	14.7

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.15: Long-term results: TFP & Exclude firms sorting

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (dummy)	-0.483	-0.426	2.74e-06
	(0.337)	(0.385)	(0.378)
Observations	115,821	115,821	115,821
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	20.7	14	14

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.16: Long-term results: TFP & TTWA x Area x Industry FEs

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (dummy)	-0.985**	-0.713	-0.707
	(0.470)	(0.473)	(0.441)
Observations	169,049	169,049	169,049
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × Area type × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	19.1	15.6	17.7

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area × Area type × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.17: Long-term results: TFP & Only 2020 WFH adopters

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (dummy)	-0.959**	-0.527	-0.564
	(0.435)	(0.410)	(0.436)
Observations	175,680	175,680	175,680
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	21.3	21.3	21.3

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

A.5 Short-term results: Heterogeneous effects

Table A.18: Short-term results: Labour productivity & Manual vs office workers

VARIABLES	(1) All firms Δ log(VA/Empl)	(2) Manufacturing Δ log(VA/Empl)	(3) KIS Δ log(VA/Empl)
WFH (dummy) × Low WFH potential	-0.722*		
	(0.382)		
WFH (dummy) × High WFH potential	-0.0431		
	(0.162)		
WFH (dummy)		-0.845**	0.00110
		(0.408)	(0.154)
Observations	104,446	24,818	26,879
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 2-digit industry fixed effects	.	✓	✓
TTWA × 4-digit industry fixed effects	✓	.	.
K-Papp F-stat	8.8	11.7	39.1

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log labour productivity. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.19: Short-term results: Labour productivity & ICTs

VARIABLES	(1) All firms Δ log(VA/Empl)	(2) >= 10 employees Δ log(VA/Empl)	(3) All firms Δ log(VA/Empl)
WFH (dummy)	-0.0823	-0.116	-0.0789
	(0.160)	(0.166)	(0.179)
Laptops per employee	-0.188	-0.362**	
	(0.139)	(0.147)	
WFH (dummy) × Laptops per employee	0.375	0.644**	
	(0.451)	(0.325)	
Servers per employee			-0.409***
			(0.136)
WFH (dummy) × Servers per employee			0.766***
			(0.282)
Observations	34,643	23,802	34,643
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	11.9	13.8	13.8

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log labour productivity. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.20: Short-term results: TFP & Firm Size

VARIABLES	(1) Δ log(TFP)	(2) Δ log(TFP)
WFH (dummy)	-0.864***	
	(0.301)	
log(Employees)	0.00604	
	(0.0179)	
WFH (dummy) × log(Employees)	0.202***	
	(0.0751)	
WFH (dummy) × Employees <= 5		-0.886***
		(0.263)
WFH (dummy) × Employees 6-10		-0.385**
		(0.174)
WFH (dummy) × Employees 11-25		-0.164
		(0.126)
WFH (dummy) × Employees >= 26		-0.0580
		(0.0772)
Observations	104,446	104,446
Firm-level controls	✓	✓
Counterfactual fibre control	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓
K-Papp F-stat	29.2	13.3

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log TFP. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.21: Short-term results: Labour Productivity & Firm Size

VARIABLES	(1) Δ log(VA/Empl)	(2) Δ log(VA/Empl)
log(Employees)	0.0471**	
	(0.0187)	
WFH (dummy)	-0.562*	
	(0.328)	
WFH (dummy) × log(Employees)	0.0910	
	(0.0803)	
WFH (dummy) × Employees <= 5		-0.941***
		(0.293)
WFH (dummy) × Employees 6-10		-0.366*
		(0.194)
WFH (dummy) × Employees 11-25		-0.0851
		(0.140)
WFH (dummy) × Employees >= 26		0.00434
		(0.0856)
Observations	104,446	104,446
Firm-level controls	✓	✓
Counterfactual fibre control	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓
K-Papp F-stat	29.2	13.3

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log labour productivity. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.22: Short-term results: TFP & Employees with postgraduate degrees

VARIABLES	(1) Δ log(TFP)	(2) Δ log(TFP)	(3) Δ log(TFP)
WFH (dummy)	0.0711	-0.0146	0.0648
	(0.187)	(0.163)	(0.187)
Master degree (share)	0.159		
	(0.0972)		
WFH (dummy) x Master degree (share)	-0.396		
	(0.283)		
MBA degree (share)		0.115	
		(0.833)	
WFH (dummy) x MBA degree (share)		0.0235	
		(2.391)	
Postgrad degree (share)			0.153
			(0.0936)
WFH (dummy) x Postgrad degree (share)			-0.370
			(0.274)
Observations	21,857	21,857	21,857
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	9.6	10	9.7

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log TFP. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

A.6 Long-term results: Heterogeneous effects

Table A.23: Long-term results: TFP & Size

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (dummy)	-2.346**	-1.590	-1.558
	(0.914)	(1.014)	(0.951)
log(Employees)	0.00295	0.00601	0.00769
	(0.0136)	(0.0122)	(0.0140)
WFH (dummy) $\times$ log(Employees)	0.537***	0.358*	0.347*
	(0.195)	(0.212)	(0.196)
Observations	162,876	162,876	162,876
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	12.6	7.6	8

Notes: This analysis is based on the full sample of firms, excluding Construction (F) and Accommodation & food service activities (I). The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.24: Long-term results: TFP & Laptops

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
Laptops per employee	0.0325	0.116	0.0800
	(0.0887)	(0.116)	(0.121)
WFH (dummy)	-0.481*	-0.208	-0.0857
	(0.288)	(0.309)	(0.283)
WFH (dummy) $\times$ Laptops per employee	0.0630	-0.743	-0.734
	(0.444)	(0.545)	(0.543)
Observations	61,663	61,663	61,663
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	8.5	6	7

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.25: Long-term results: TFP & Servers

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
Servers per employee	-0.164*	-0.108	0.00151
	(0.0984)	(0.0932)	(0.114)
WFH (dummy)	-0.536	-0.354	-0.193
	(0.333)	(0.374)	(0.331)
WFH (dummy) $\times$ Servers per employee	0.356	0.0328	-0.324
	(0.384)	(0.346)	(0.398)
Observations	61,519	61,519	61,519
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	7.5	5.3	6.5

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.26: Long-term results: TFP & WFH potential

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (dummy) $\times$ Low WFH potential	-1.177*	-0.926	-0.671
	(0.642)	(0.615)	(0.579)
WFH (dummy) $\times$ High WFH potential	-0.336	0.113	-0.0756
	(0.261)	(0.291)	(0.353)
Observations	178,930	178,930	178,930
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	6.2	5.7	5.6

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.27: Long-term results: TFP & Manufacturing

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH	-0.410	-0.0342	-0.484
	(0.366)	(0.435)	(0.362)
Observations	54,276	54,276	54,276
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	7	6.1	12.3

Notes: This analysis is based on the sample of firms operating in the manufacturing sector. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.28: Long-term results: TFP & KIS

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH	-0.0989	-0.0553	-0.121
	(0.165)	(0.415)	(0.634)
Observations	20,918	20,918	20,918
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	20.8	3.8	2.4

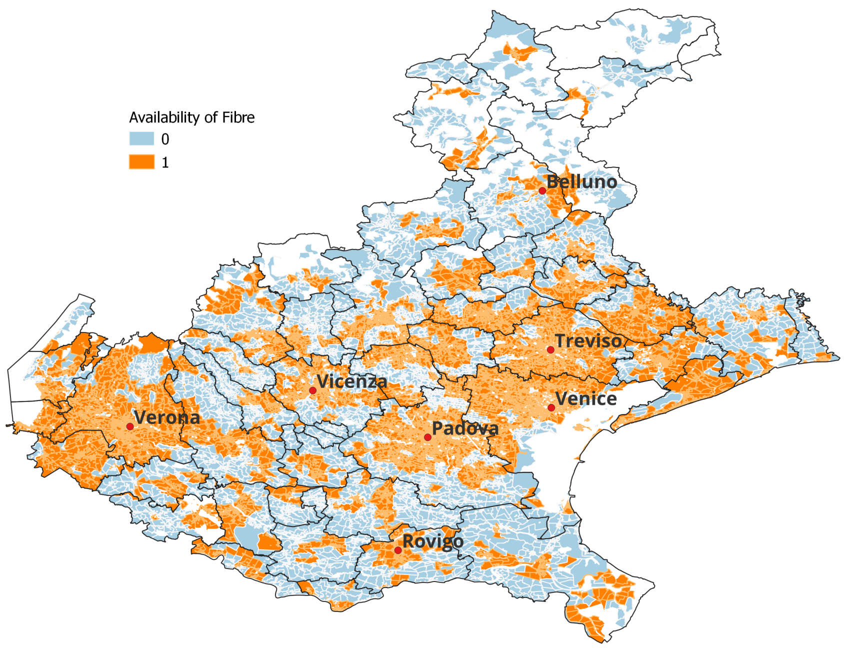
Notes: This analysis is based on the sample of firms operating in the manufacturing sector. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

B Additional Figures

Figure B.1: Location of optical packet backbone nodes

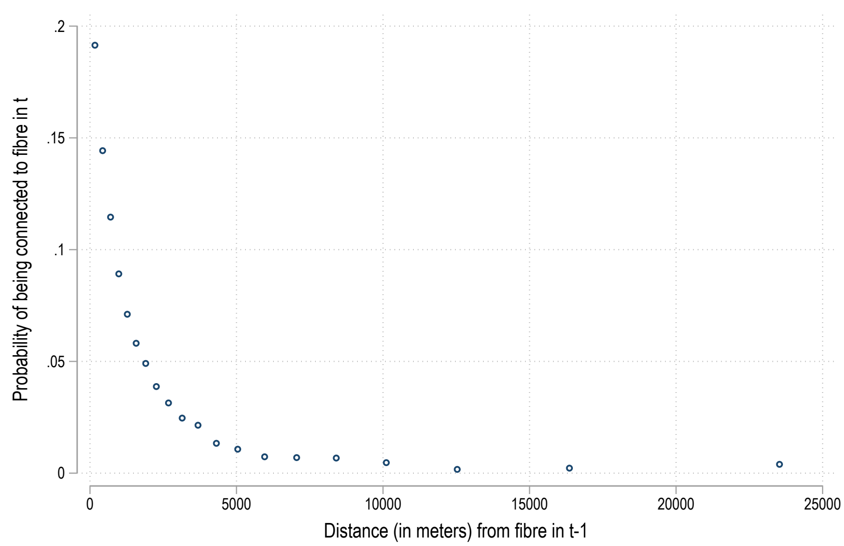
Notes: The figure shows the map of Italy and the location of the 35 optical packet backbone nodes.

Figure B.2: Example of fibre broadband coverage, by TTWA and census tract



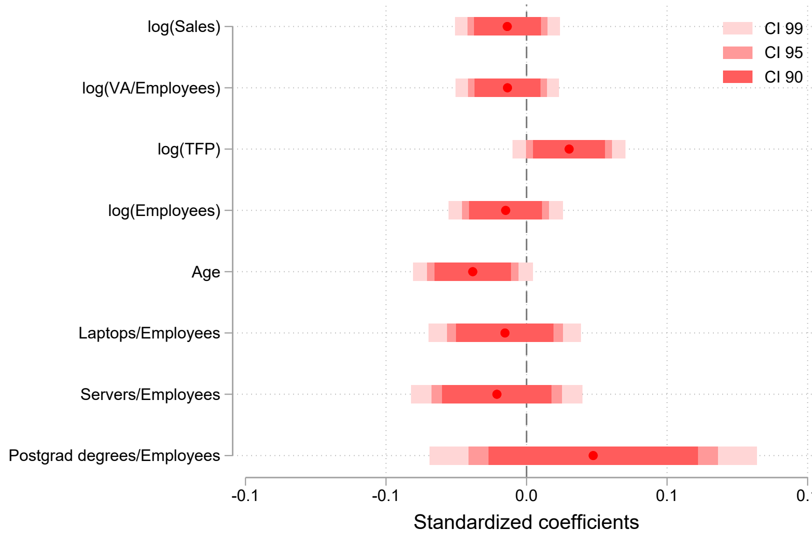
Notes: The figure shows fibre coverage at the census tract level for the NUTS-2 region of Veneto. Areas with fibre coverage are shown in orange, while those without are in blue. The black polygons correspond to travel-to-work-areas and white polygons to census tract boundaries.

Figure B.3: Adjacent roll-out and distance



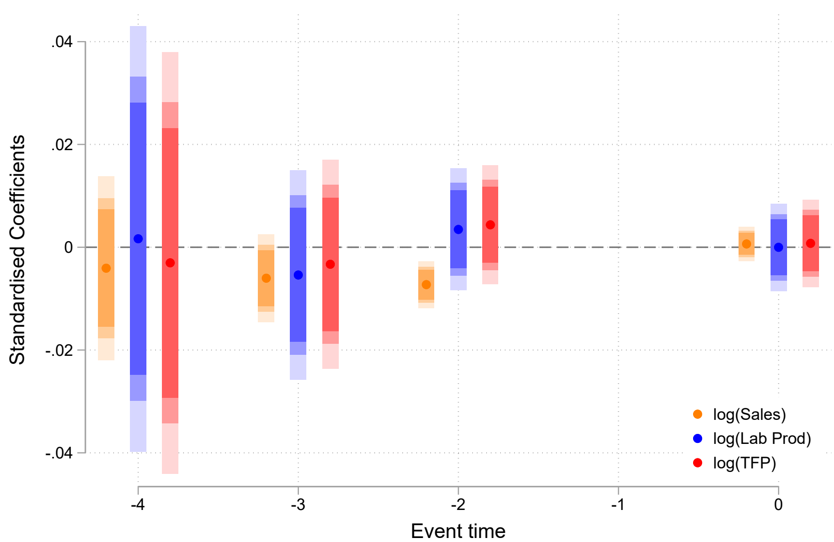
Notes: The figure plots the relationship between the geographical distance (in meters) between a census tract not covered by fibre in year t and the closest census tract covered by fibre in t-1 (horizontal axis) and a variable that equals one if the census tract is covered by fibre in t.

Figure B.4: Balancing tests



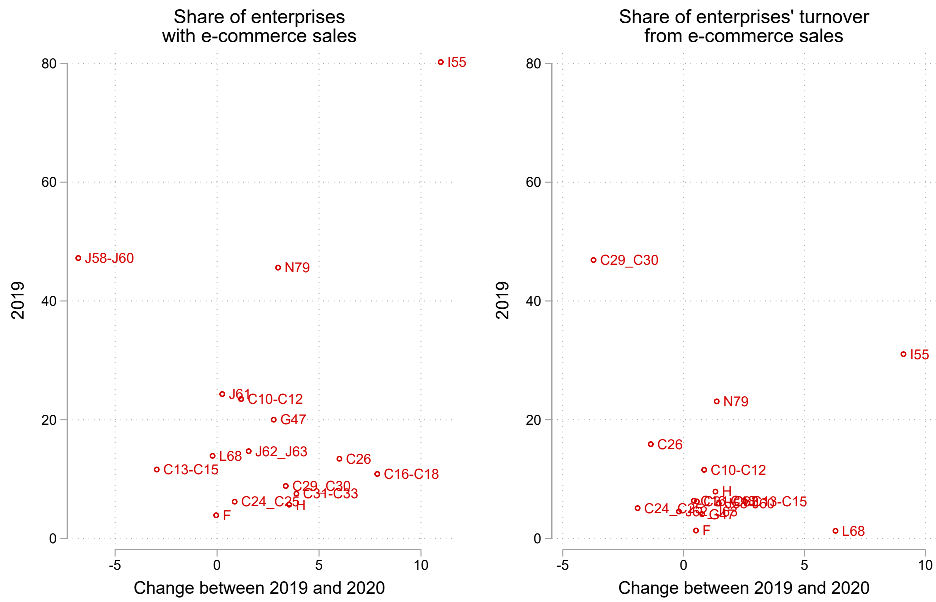
Notes: This analysis is based on the whole sample of firms in 2019. The figure presents the point estimates and their 90, 95 and 99% confidence intervals for the balancing tests. Treated units (firms with access to fibre) and control units (firms without access to fibre) do not significantly differ across firm characteristics when the confidence intervals intersect zero.

Figure B.5: Pre-trends with timing of fibre deployment



Notes: This analysis is based on the whole sample of firms in the 2015-2019 period. The figure presents the point estimates and their 90, 95, 99% confidence intervals of event study regressions for log sales, log labour productivity and log TFP in periods before fibre enablement. Estimation follows Callaway and Sant'Anna, 2021, estimating enablement-firm by cohort compared to never fibre enabled firms.

Figure B.6: E-commerce adoption, by NACE 2-digit industries



Notes: The figure plots the relationship between the change in share from 2019 to 2020 (horizontal axis) and the share in 2019 (vertical axis). The left panel shows the share of enterprises with e-commerce sales, while the right panel the share of enterprises' turnover from e-commerce sales, both measured at the 2-digit NACE level.

C Results for WFH intensive margin

In this section, we present the results of equation 1 and 2 using the share of employees in WFH as proxy for firm's WFH adoption.

Table D.1: Short-term OLS results

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (share)	0.0603***	0.105***	0.0933***
	(0.00485)	(0.00635)	(0.00579)
Observations	104,446	104,446	104,446
R-squared	0.258	0.237	0.231
Firm-level controls	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log labour productivity in column 2 and log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.2: Short-term IV results

VARIABLES	(1) Δ log(Sales)	(2) Δ log(VA/Empl)	(3) Δ log(TFP)
WFH (share)	0.225	-0.574**	-0.625**
	(0.230)	(0.292)	(0.263)
Expected fibre	-0.00821	-0.00484	-0.00227
	(0.00876)	(0.0110)	(0.0101)
Observations	104,446	104,446	104,446
R-squared	0.010	-0.064	-0.152
Firm-level controls	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	55.3	55.3	55.3

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log sales in column 1, log value added in column 2 and log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.3: Long-term results: TFP

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (share)	-1.189**	-0.844	-0.814
	(0.533)	(0.628)	(0.652)
Observations	178,930	178,930	178,930
R-squared	-0.225	-0.035	0.004
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	37.4	28.4	27.7

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table D.4: Short-term results: TFP & Manual vs office workers

VARIABLES	(1) All firms Δ log(TFP)	(2) Manufacturing Δ log(TFP)	(3) KIS Δ log(TFP)
WFH (share) × Low WFH potential	-2.268**		
	(1.082)		
WFH (share) × High WFH potential	-0.0624		
	(0.184)		
WFH (share)		-1.703**	-0.112
		(0.707)	(0.142)
Observations	104,446	24,818	26,879
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 2-digit industry fixed effects	.	✓	✓
TTWA × 4-digit industry fixed effects	✓	.	.
K-Papp F-stat	6.1	19.9	43.5

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log TFP. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table D.5: Short-term results: TFP & Investments in ICTs

VARIABLES	(1) All firms Δ log(TFP)	(2) >= 10 employees Δ log(TFP)	(3) All firms Δ log(TFP)
WFH (share)	0.0333	0.0125	0.0119
	(0.324)	(0.386)	(0.377)
Laptops per employee	-0.0933	-0.222*	
	(0.106)	(0.115)	
WFH (share) × Laptops per employee	0.367	0.574	
	(0.514)	(0.387)	
Servers per employee			-0.304**
			(0.122)
WFH (share) × Servers per employee			0.719**
			(0.322)
Observations	34,643	23,802	34,643
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	10.6	9.5	11.1

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log TFP. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.6: Short-term results: TFP & Firm Size

VARIABLES	(1) Δ log(TFP)	(2) Δ log(TFP)
WFH (share)	-1.124***	
	(0.406)	
log(Employees)	0.0135	
	(0.00848)	
WFH (share) × log(Employees)	0.249***	
	(0.0852)	
WFH (share) × Employees <= 5		-1.123***
		(0.352)
WFH (share) × Employees 6-10		-0.521**
		(0.251)
WFH (share) × Employees 11-25		-0.231
		(0.204)
WFH (share) × Employees >= 26		-0.0856
		(0.158)
Observations	104,446	104,446
Firm-level controls	✓	✓
Counterfactual fibre control	✓	✓
TTWA × 4-digit industry fixed effects	✓	✓
K-Papp F-stat	28.9	13.8

Notes: This analysis is based on the sample of firms operating in essential industries. The dependent variable is the 2019-2020 change in log TFP. All specifications include travel-to-work area × 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area × 4-digit industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table D.7: Long-term results: TFP & Postgraduate degrees

VARIABLES	(1) 2019-2020 Δ log(TFP)	(2) 2019-2021 Δ log(TFP)	(3) 2019-2022 Δ log(TFP)
WFH (share)	-0.136	0.314	-0.263
	(0.404)	(0.435)	(0.513)
Postgrad degrees (share)	-0.0416	-0.0526	-0.156***
	(0.0534)	(0.0481)	(0.0558)
WFH (share) $\times$ Postgrad degrees (share)	0.453	0.214	0.970**
	(0.388)	(0.405)	(0.412)
Observations	24,168	24,168	24,168
R-squared	0.027	0.020	0.053
Firm-level controls	✓	✓	✓
Counterfactual fibre control	✓	✓	✓
TTWA $\times$ 4-digit industry fixed effects	✓	✓	✓
K-Papp F-stat	5.8	6.3	5.2

Notes: This analysis is based on the full sample of firms. The dependent variable is the 2019-2020 change in log TFP in column 1, the 2019-2021 change in log TFP in column 2 and the 2019-2022 change in log TFP in column 3. All specifications include travel-to-work area $\times$ 4-digit industries fixed effects as well as a set of firm-level controls taken in the year 2019 (including log employees, log value added per employee and age). Standard errors are clustered at the travel-to-work area $\times$ 4-digit industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

D Data appendix

In this section, we describe the data sources used in our analysis and the procedure we use to merge them and clean the resulting dataset.

D.1 WFH data

Legal framework. In Italy, *lavoro agile* (also called smart working) was introduced by Law 81/2017 (Arts. 18–24). The law requires employers to communicate smart-working arrangements to the Ministry of Labour and Social Policies (MLPS) to ensure INAIL insurance coverage for work injuries occurring away from the employer's premises. This requirement was fulfilled by a telematic notification of a written agreement between the employer and employee through the MLPS dedicated online portal. From 1 March 2020, in response to the COVID-19 pandemic, a simplified procedure applied nationwide: employers had to communicate workers in smart working by filing an online excel form via the MLPS portal. From 1 September 2022, this emergency regime was made structural by Ministerial Decree No. 149/2022, asking employers to continue transmitting via the MLPS online system. At this link an example of the one-page form that firms are required to fill out. Substantively, therefore, the pandemic-era procedure became the official channel, so nothing has changed in the communication workflow since then.

Failure to make the mandatory MLPS communication is punishable by an administrative fine that depends on the scale of the violation. For example, if the violation concerns more than ten workers, the fine ranges from 1,000 to 5,000 euros per worker for each month of failure to declare.[20] Given the magnitude of the sanction and the low administrative burden of the online procedure, this regime creates strong incentives for compliance.

Cleaning. These real time data are of high quality and require little cleaning. To construct our measures, we perform the following cleaning steps: (i) drop records with miss-

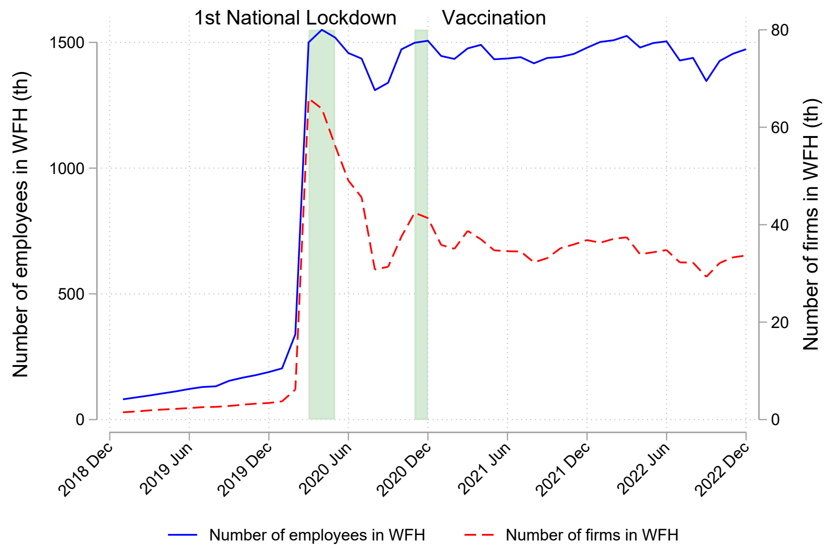
[20] This is stipulated by the Legislative Decree No. 276/2003 at this link.

ing firm ID or worker ID; (b) enforce valid date order (end $\geq$ start); (c) cap implausibly end dates (year end ≤ 2024) and start dates (year start ≥ 2017); (d) merge adjacent spells with ≤ 2-day gaps for the same worker–firm (usually referring to the weekend).

Summary statistics. We present stylised aggregate evidence on the uptake of WFH during the COVID-19 emergency and its evolution beyond the pandemic period. During the first lockdown in March–May 2020 around 1.7 million workers were working from home and approximately 72,000 private firms had at least one employee working remotely (Figure C.1). With the onset of the national lockdown on March 9th, the number of employees in WFH rose exponentially: from roughly 200,000 at the beginning of the year to more than 1.5 million by the end of March.

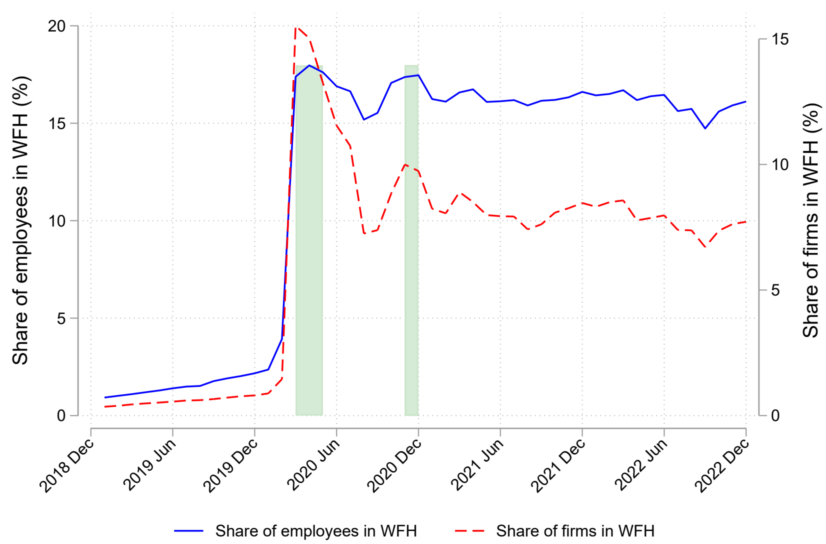
Figure C.2 reports the share of employees and firms adopting WFH, using Orbis as the reference population of workers and firms. The share of employees working remotely in our data was 2.1% in 2019, while peak adoption in 2020 is measured at 17.6%. Italy recorded one of the largest increases in both workers and firms switching to WFH during the pandemic (Eurofound, 2020), making it an ideal empirical setting to study the effects of remote work. In the post-pandemic period, while the number of employees working remotely remained broadly stable until the end of 2022, the number of firms declaring WFH slightly declined. By December 2022, about 35,000 firms continued to report employees working from home.

Figure C.1: Number of workers and firms adopting WFH, January 2019 - December 2022



Notes: This figure shows the number of monthly workers and firms adopting WFH. Firms operating in A, B, O, P, Q, R, S, T and U, and self-employed are excluded consistently with the baseline analysis. The green vertical areas indicate the first national lockdown in March-May 2020 and the start of the administration of the vaccine in December 2020.

Figure C.2: Share of workers and firms adopting WFH, January 2019 - December 2022



Notes: This figure shows the share of monthly workers and firms adopting WFH. Firms operating in A, B, O, P, Q, R, S, T and U, and self-employed are excluded consistently with the baseline analysis. The green vertical areas indicate the first national lockdown in March-May 2020 and the start of the administration of the vaccine in December 2020.

Table C.1 shows summary statistics on WFH by 1-digit ATECO rev. 2 industries in

2020. The industries with the largest shares of firms and workers in WFH are knowledge-intensive services industries, such as energy (D), information & communication (J), financial & insurance (K) and professional activities (M). This finding is in line with studies showing that high-skilled intensive occupations (e.g. managers and professionals) rely the most on WFH practices (Alipour, Fadinger, & Schymik, 2021; Crescenzi, Giua, & Rigo, 2022; Mongey & Weinberg, 2020).

Table C.1: Summary statistics on WFH by 1-digit NACE rev. 2

NACE 1-digit	Description	Sh firms in total	Sh firms in WFH	Sh Employees in total	Sh Employees in WFH
C	Manufacturing	0.23	0.16	0.35	0.14
D	Electricity, gas, steam & air conditioning supply	0.00	0.30	0.01	0.52
E	Water supply; sewerage & waste management	0.01	0.17	0.02	0.14
F	Construction	0.15	0.05	0.08	0.05
G	Wholesale & retail	0.26	0.08	0.18	0.10
H	Transportation & storage	0.05	0.08	0.09	0.15
I	Accommodation & food service activities	0.09	0.01	0.06	0.01
J	Information & communication	0.05	0.33	0.05	0.65
K	Financial & insurance	0.01	0.23	0.01	0.36
L	Real estate activities	0.03	0.09	0.01	0.14
M	Professional, scientific & technical activities	0.06	0.28	0.04	0.46
N	Administrative & support service activities	0.05	0.13	0.09	0.18

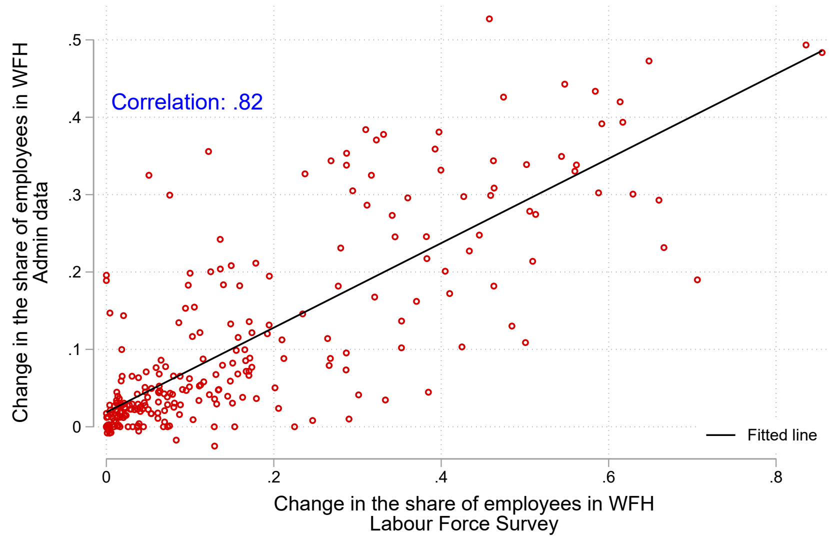
Notes: The Table presents summary statistics at the 1-digit NACE industry level for the full sample of firms in 2020. These statistics are based on the whole sample of firms matched with the Orbis data, including both essential and non-essential industries.

Validation. Given strong compliance incentives, coverage should be near-exhaustive for private-sector employees. We validate our data against the EU Labour Force Survey (LFS). The LFS is a national household survey on labour participation published by Eurostat, covering people aged 15 and above, representative of the Italian population at the 2-digit NUTS $\times$ 1-digit industry level. Figures C.3 and C.4 compare the share of employees in WFH calculated at the 2-digit NUTS (equivalent to Italian provinces) $\times$ 1-digit industry level. We find that the WFH data are highly collinear with the LFS: the correlation between the two sets of data stands at 84% in 2020 levels, and at 82% in 2019-2020 changes.

Figure C.3: Validation WFH Admin versus LFS - Levels

Notes: The figure plots the relationship between the share of employees in WFH based on the Labour Force Survey (horizontal axes) and the share of employees in WFH based on our admin data (vertical axes). Shares are calculated as the ratio of employees working from home at least a few days a week and the total number of employees at the 2-digit industry and NUTS-2 regional level for the year 2020.

Figure C.4: Validation WFH Admin versus LFS - Changes



Notes: The figure plots the relationship between the change in the share of employees in WFH based on the Labour Force Survey (horizontal axes) and the change in the share of employees in WFH based on our admin data (vertical axes). Changes are calculated as the difference in the WFH share between 2020 and 2019 at the 2-digit industry and NUTS-2 regional level.

D.2 Orbis data

Coverage. We use *Orbis Historical*, from Moody's Analytics, to obtain firm-level accounts and locations for Italy. Our work relies on the August 2025 version of the data, which allows to follow firms over time up to the year 2022. We exclude 2023 because financial statements present a lag (of roughly two/three years) driven by statutory filing deadlines and registry processing; as a result, balance sheet data for 2023 remain yet incomplete. As shown in Table C.2, since 2015 the coverage has been quite consistent, with roughly 550 thousand observations available in the data in 2022.

Table C.2: Number of observations in Orbis data, by year

	Raw		Cleaned	
Year	Freq.	Percent	Freq.	Percent
2015	494,273	11.99	449,446	11.90
2016	499,115	12.11	455,746	12.07
2017	505,668	12.27	462,440	12.24
2018	509,408	12.36	468,237	12.40
2019	524,908	12.73	483,331	12.80
2020	508,766	12.34	456,807	12.09
2021	531,012	12.88	491,752	13.02
2022	548,630	13.31	509,534	13.49
Total	**4,121,780**	**100.00**	**3,777,293**	**100.00**

Notes: The table reports the distribution of observations by year in our Orbis Historical raw sample (column 2-3) and cleaned sample (column 4-5).

Cleaning. Cleaning the data from outliers is essential, as extreme or erroneous values in firm accounts can severely distort our analysis. Table C.2 reports the number of observations in our sample after the cleaning steps detailed below. To clean the data, we follow and extend the Kalemlİ-Özcan et al., 2024 and Bajgar et al., 2020 cleaning procedure as follows:

- Drop firm-year with missing information on number of employees, value added, sales, total asset or material costs.
- Keep accounts that refer to entire calendar years.

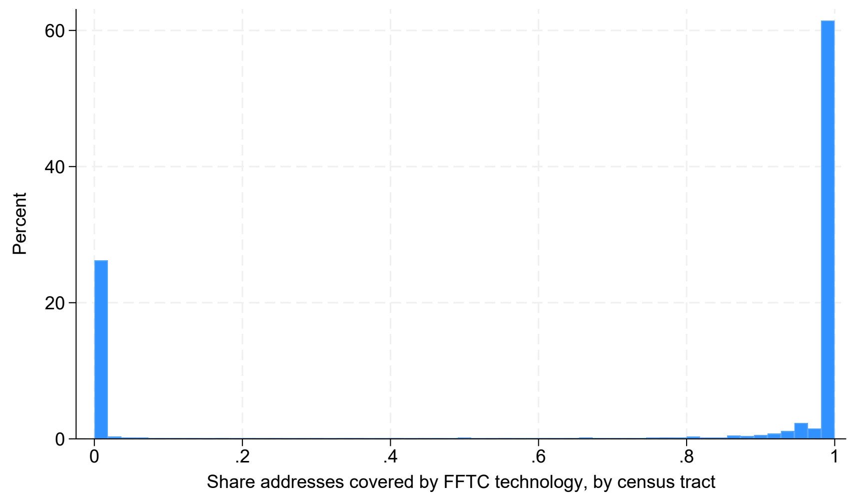
- Exclude consolidated accounts (C1 or C2).
- Exclude accounts with limited financial information (LF).
- Deal with outliers as follows:
  - Drop the entire firm (all years) if total assets, employment or sales are negative in any year.
  - Drop the entire firm when reporting in any year a value of employment per million of total assets larger than the 99.9 percentile of the distribution.
  - Drop the entire firm when reporting in any year a value of employment per million of sales larger than the 99.9 percentile of the distribution.
  - Drop the entire firm when reporting in any year a value of sales to total assets larger than the 99.9 percentile of the distribution.
  - Drop the entire firm when reporting in any year a ratio of sales, number of employees or value added to the previous year that is larger than the 99.9 percentile of the distribution.
- Deal with firm-year duplicates (few cases) by keeping the ones with largest employment, value added or sales.
- Exclude inactive firms.

D.3 Broadband data

We use annual broadband-coverage data web-scraped from Infratel Italia. Italian fixed-line operators are formally requested to provide current fibre coverage and three-year plans through Infratel's platform; on mandate from the Ministry (MiSE/MIMIT) and in line with the EU State-aid broadband mapping guidelines. As a result, the broadband coverage dataset is designed to be exhaustive.

We link these data to official tract boundaries and assign firms to tracts using their geocoded addresses. Italy has 402,678 census tracts, with a mean population of 162 individuals in 2011. We classify a census tract as fibre-available, when the share of buildings covered by FTTC technology is higher than 75%, motivated by a highly bimodal distribution (Figure C.5).

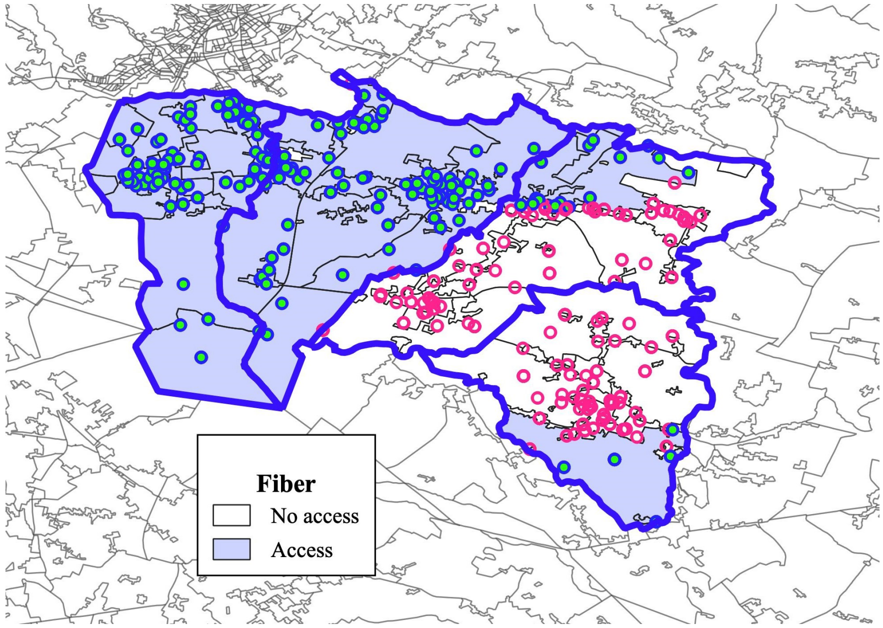
Figure C.5: Coverage FFTC technology, by census tract



Notes: The figure shows the share of addresses covered by FTTC technology across census tracts in 2019.

To highlight the granularity of our data, Figure C.6 illustrates the case of four neighbouring municipalities - Santa Lucia di Piave, Mareno di Piave, Vazzola and San Polo di Piave - each with fewer than 10,000 inhabitants as of 2023. Thanks to the high spatial resolution of our broadband coverage measure, we are able to detect whether firms have access to fibre even within the same (small) municipality.

Figure C.6: Example of fibre broadband coverage, by census tract



Notes: The figure shows fibre coverage at the census tract level for four municipalities: Santa Lucia di Piave, Mareno di Piave, Vazzola, San Polo di Piave (from left to right). Areas with fibre coverage are shown in blue, while those without are in white. Each dot represents a firm, and the polygons correspond to census tract boundaries.

Table C.3 shows the share of firms with access to fibre technology in 2019 across Italian industries (1-digit) and regions (1-digit) and by firm's size class (micro, small, medium and large). The availability of fibre technology (at least 30 Mbps) is quite high, with 86% of Italian firms with access to fibre. Larger firms and companies operating in knowledge-intensive industries (such as financial services) have higher access to a fast internet connection, consistent with the fact that these firms are usually located in more urbanised areas.

Table C.3: Share of firms with access to fibre

	All	Micro	Small	Medium	Large
All	0.86	0.86	0.83	0.83	0.88
Region (1-digit)					
South	0.85	0.85	0.84	0.84	0.87
Center	0.87	0.87	0.84	0.84	0.89
North	0.86	0.86	0.82	0.82	0.89
Industry (1-digit)					
Manufacturing	0.78	0.79	0.76	0.74	0.82
Energy	0.82	0.79	0.81	0.87	0.83
Construction	0.83	0.82	0.81	0.83	0.87
Non-financial services	0.89	0.89	0.89	0.89	0.89
Type of location					
Residential area	0.90	0.92	0.88	0.90	0.88
Mountain area	0.66	0.73	0.64	0.65	0.66
Industrial area	0.79	0.81	0.76	0.81	0.78
Rural area	0.64	0.67	0.63	0.64	0.63

Notes: The Table presents the share of firms with access to fibre by firm size, macro region (North, Centre, South), 1-digit NACE industry level, and type of census tract (residential, industrial, mountain, rural).

D.4 ICT data

Our source of data on ICTs is the Aberdeen Computer Intelligence Database (CiTDB) provided by Spiceworks Ziff Davis Aberdeen Group. Using a unique tax identifier (available for roughly 25% of firms in the ICT dataset) and a fuzzy-matching procedure, we link the ICT dataset to our firm-level data. Matching relies on the company name and address information. We retain only candidate matches with a name-similarity score above 90% and select the best match as the candidate with the highest address score.

However, the ICT dataset has only partial coverage and is biased towards larger firms. As shown in Table C.4, matched firms tend to be larger, older, more productive and more likely to adopt WFH than the full sample.

Table C.4: Matching statistics, ICT data subsample, 2022

	Mean (Baseline)	Mean (ICT)	P-value
Δ log Sales	0.19	0.18	***
Δ log VA per employee	0.16	0.15	***
Δ log TFP	-0.02	-0.02	***
No of Employees	2.06	2.74	***
Age	15.53	22.78	***
VA per employee (log)	10.61	10.93	***
WFH(share)	0.04	0.06	***
Fibre	0.87	0.83	***

Notes: These descriptive statistics are based on the whole sample of firms in 2022. Δ denotes the 2019-2022 change. The variable in levels are instead taken in the year 2019, including number of employees, age (in years) and value added per employee (in log). The table reports the variables' means in the main sample and in the subsample. The last column reports the significance of a mean difference test between the two samples; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

D.5 E-commerce data

Information on firms' e-commerce activities is obtained from BuiltWith. The BuiltWith data are available for the near universe of websites around the world (roughly 550 million websites) and have been collected in the same manner from 2018 onwards. BuiltWith scrapes the source-code information embedded in websites across the globe every 1 to 4 weeks. The set of websites is obtained from public secure socket layer (SSL) lists on a monthly basis. This became a de-facto public ledger of all secure websites (i.e. those with SSL certificates) since becoming a Google Chrome requirement in April 2018, so-called Certificate Transparency.

However, measures of e-commerce embedded in a firm's website are likely to be a lower bound since firms can engage in e-commerce by using social media or other digital platforms rather than through their website. However, while data on platform use is scarce, firm websites appear to reflect the bulk of e-commerce activity and there is no evidence of greater use of platforms as opposed to own websites in Italy. In Europe, nearly 90% of firm e-commerce sales are through their website rather than a platform, while even for small firms, sales through their website account for 80% of e-commerce (European Commission, 2024).

D.6 LinkedIn data

Coverage. The presence of individuals' profiles on LinkedIn varies greatly by occupation, location and time. However, individuals with a college education and those in white-collar jobs are more likely to have a LinkedIn profile compared to those without higher education or in blue-collar positions. Amanzadeh and McQuade, 2024 confirms that LinkedIn coverage in Italy is exceptionally comprehensive, nearing 100% when compared to International Labour Organization (ILO) figures. Additionally, the LinkedIn data coverage is most extensive for the years relevant to our analysis (from 2019 onwards). Lastly, as an internal validation of the quality of the LinkedIn-based measures, Crescenzi, Dottori, and Rigo, 2025 use administrative employer–employee matched data for Italy and document a strong correlation between the share of workers holding an MBA or university degree on LinkedIn and the share of white-collar employees or managers recorded in administrative sources. Therefore, we consider LinkedIn as a representative source of information on the management quality of Italian companies.

Cleaning. We clean the LinkedIn raw data from Revelio Labs as follows:

- For each individual, we classify their highest degree (MBA, Master's, Bachelor's) based on keyword lists extracted from their educational background.
- We construct a yearly panel, using the start and end dates of each job spell.
- For each company, individuals are assigned to the position in which they spent the most time. In the event of ties, the position with the longest tenure takes precedence.

Because employment and education records are self-reported, there is always the possibility that individuals provide inaccurate details. Although the data do not allow for a direct test of misreporting, we argue that the incentive to falsify information on a public

LinkedIn profile is limited. Users face the credible risk of account suspension if discrepancies are reported, as LinkedIn enables others to flag profiles that contain misleading information. This creates a strong deterrent against inflating or fabricating credentials.

Matching procedure. We focus on the year 2019 and link the LinkedIn data to Orbis using a fuzzy matching procedure. This method compares company names, URLs (when available), and locations to identify the closest matches based on similarity scores. The procedure is as follows:

- Name match: retain only candidates with a similarity score above 90.
- URL match: when available, retain only candidates with a similarity score above 95.
- Candidates must satisfy at least one of these two criteria to be considered a potential match
- For all qualified candidates, we compute the location similarity and then calculate the mean of available scores (URL, name, location), considering the highest score between URL and name.
- Final selection: we keep only candidates with a mean score above 90 and choose the one with the highest mean as the best match.

Matching statistics. We report statistics on the matching between Orbis and LinkedIn data. The LinkedIn data has a partial coverage and tends to be skewed towards larger firms. As shown in Table C.5, with respect to the main sample, matched firms tend to be larger, older, more productive and more likely to adopt WFH compared with the main sample.

Table C.5: Matching statistics, 2022

	Mean (Baseline)	Mean (LinkedIn)	P-value
Δ log Sales	0.19	0.21	***
Δ log VA per employee	0.16	0.14	***
Δ log TFP	-0.02	-0.03	***
No of Employees	2.06	2.78	***
Age	15.53	19.58	***
VA per employee (log)	10.61	10.92	***
WFH(share)	0.04	0.12	***
Fibre	0.87	0.88	***

Notes: These descriptive statistics are based on the whole sample of firms in 2022. Δ denotes the 2019-2022 change. The variable in levels are instead taken in the year 2019, including number of employees, age (in years) and value added per employee (in log). The table reports the variables' means in the main sample and in the subsample. The last column reports the significance of a mean difference test between the two samples; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.