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WORKING FROM HOME AND LABOUR PRODUCTIVITY: FIRM-LEVEL EVIDENCE

by Gaetano Basso*, Davide Dottori* and Sara Formai*

Abstract

This study examines the impact of working from home (WFH) on firm-level outcomes. It uses detailed survey, balance sheet and matched employer-employee data on Italian firms from before the pandemic and up to 2023. Estimates using a novel instrumental variable suggest that, on average, the effects on labour productivity, employment dynamics and composition, wages and other costs are negligible. However, the analysis shows that results are heterogeneous across firms. For some firms, whose labour productivity did not decline, the pandemic-induced shift to WFH was maintained after the emergency ended.

JEL Classification: D24, J24, J81, O33, D22, L23.

Keywords: working from home, firm organization, labour productivity.

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1 Introduction*

Firms were reluctant to adopt working from home (WFH) before the Covid-19 pandemic due to frictions related to internal organization and uncertainty about its effects on labour productivity (Barrero, Bloom, and Davis, 2023). At the onset of the pandemic, the difficulty of performing work using traditional methods —and, in particular, physical presence— put economic activity at risk. Early evidence from the pandemic showed that WFH helped limit negative impacts on labour input and output, although the effect varied across firms (Basso and Formai, 2021). Widespread adoption of WFH was more common among firms where on-site work was less essential (e.g., IT, financial, and professional services) and among those with higher investments in ICT technologies. A more favorable skill composition of the workforce (Barrero et al., 2023; Bloom, Han, and Liang, 2023) and superior managerial practices (Lamorgese, Linarello, Schivardi, and Patnaik, 2024) may also have boosted the gains from WFH. In contrast, the lack of preparation and adequate technical resources at the onset of the pandemic may explain negative productivity effects (Gibbs, Mengel, and Siemroth, 2023; Boeri, Crescenzi, and Rigo, 2025).

However, it remains unclear whether the frictions that prevented adoption before 2020 have been alleviated. Although some commentators claimed that WFH is here to stay, citing benefits for both firm productivity and worker welfare (Angelici and Profeta, 2023; Barrero et al., 2023; Barrero, Bloom, and Davis, 2021; Choudhury, Khanna, Makridis, and Schirmann, 2024; Bergeaud, Cette, and Drapala, 2024), others reported null or negative impacts on firm performance and worker productivity (Emanuel and Harrington, 2024) or highlighted high costs for worker welfare and health (Choudhury et al., 2024). Evidence based on hard data for representative sets of firms is still scarce and the medium-run persistence of WFH and its effects on labour productivity remain uncertain.[1]

In this paper, we analyze the use of WFH since 2019 and its impact on firm-level labour productivity, using a rich set of administrative and survey data on Italian firms. First, we characterize the determinants of WFH adoption up to 2023. Based on this evidence, we isolate a plausibly exogenous source of variation stemming from the interaction between the sectoral share of jobs that can be performed from home and the local availability of high-speed broadband internet. We then relate the change in WFH after the pandemic to firm labour productivity and its components (revenues, quantities, headcount employment, and hours worked) for

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[1]Fenizia and Kirchmaier (2025) represents a recent exception, but focus on the public sector only.

a large sample of industrial and service firms with at least 20 employees obtained from the Banca d'Italia's Survey of Industrial and Service Firms (INVIND). The survey collects data on the percentage of employees working from home from 2019 to 2023.

Several channels influence how WFH arrangements affect firm productivity, with both positive and negative implications. On the one hand, increased flexibility and autonomy can enhance employee motivation and improve work-life balance, potentially translating into greater work effort. On the other hand, productivity may decline if reduced direct monitoring leads to a lower focus and increased distractions. In addition, slower interactions among colleagues can hinder mentoring, learning, and coordination, thereby raising communication costs. Another key factor is the impact of WFH on firms' cost structures, particularly through reductions in real estate expenses. Additionally, remote work can accelerate the adoption of digital technologies, generating broader positive spillovers across the firm's production processes.

In the first part of the paper, we analyze a panel of firms from 2019 to 2023 and describe the usage of WFH based on a wide array of firms, workforce, and geographic characteristics. In the second part, we tackle the causal impact of WFH on firm labour productivity and its components during the pandemic years and afterward. In order to overcome endogeneity issues due to firm-specific characteristics, we instrument the change in WFH after the pandemic with the interaction between the workforce's WFH-preparedness —measured at the sectoral level to avoid firm-specific selection— and the local availability of high-speed broadband Internet, as recorded in administrative data. Both components are measured in 2019, thus being pre-determined with respect to the Covid-19 shock. At the onset of the pandemic, the joint realization of these two conditions enabled some firms to adopt WFH more swiftly when the crisis hit in 2020 (Barrero et al., 2023). Our identification strategy controls for observable determinants of WFH (measured before the shock), as well as for the two individual components of our instrumental variable. Moreover, by taking differences between the pre- and post-pandemic periods, we further control for time-invariant firm characteristics. We provide several tests to validate our IV identification strategy.

Italy represents a very interesting case to study given the sharp and substantial increase in WFH induced by the pandemic. In 2019 working from home was rare: according to our data, only 9.8% of firms were using it. On average, just 1.2% of workers worked remotely on a daily basis. The pandemic triggered a sharp increase in WFH: 58.6% of firms used it in 2020 —a 49 percentage point increase in one year— with the intensive margin increasing to an average of 14.7%. After its peak, the prevalence of WFH declined; by 2023, only 28% of firms reported using it to some extent, with the average intensity falling by 10% to around 4.5%. Despite this normalization, many firms maintained WFH as a long-term practice, with a high persistence between 2021 and 2023. These aggregate trends mask significant variation across firms. Sectoral differences were stark, with 74% of IT services firms and 65% of professional services firms adopting WFH, compared to only 6% in accommodation and food services. In both 2021 and 2023, higher adoption was associated with a greater share of remote-capable jobs (Basso, Boeri, Caiumi, and Paccagnella, 2022), greater reliance on cloud technologies, a higher proportion of female workers, higher wages, and increased R&D investment. Moreover, structured managerial practices (Bloom and Van Reenen, 2007; Lamorgese et al., 2024) appear to facilitate WFH adoption.

Regarding causal analysis, we find economically and statistically average null effects of WFH on labour productivity (irrespective of whether measured in revenue or quantity terms) and its components (revenues, quantities, headcount employment and hours worked). Despite the first-stage being above conventional levels, we also employ a partial identification approach to address issues of potential imprecision (Andrews, Stock, and Sun, 2019). This method excludes effects smaller than -0.7% and larger than 1.0% between 2019 and 2023. For the average firm, we further find null effects on workforce composition and average wage, variable costs, and ITC investments.

Taken together, the contrast between the widespread adoption of WFH and its persistence after the pandemic, on the one hand, and the lack of impact on various firm-level outcomes, on the other hand, suggests that the "mass social experiment in working arrangements" (Barrero et al., 2023) alleviated some frictions to the use of WFH. The average firm learn that WFH adoption does not hurt in terms of labour productivity. To further explore this issue, we examine firm-level heterogeneity in WFH adoption to determine whether the zero effects hide underlying differences across firms. We estimate marginal treatment effects à la Heckman and Vytlacil (1999, 2007). Relating the heterogeneity in the treatment effect to the observed and unobserved heterogeneity in firms' aversion to adopt WFH (i.e., resistance in the marginal treatment effects terminology), we find that a subset of firms with a low-to-medium aversion experienced a small positive effect on labour productivity and was more likely to maintain WFH arrangements after the pandemic was over. Conversely, firms whose frictions to adopt were the highest experienced negative effects on labour productivity and also went back to more traditional work arrangements once the emergency ended.

We tested for channels other than frictions to WFH adoption, such as persistence due to cost-saving practices by firms and investments inside the organizations to facilitate remote work and improve its effectiveness. We do not find evidence for alternative stories, except for firms with prior investments in digital technologies that also experienced labour productivity gains as they adopted more WFH arrangements.

There are three main areas in which this paper contributes to the literature. First, we document the determinants of WFH adoption both during and after the pandemic using a unique mix of matched administrative and survey data, which cover firms' balance sheets, workforce composition, and geographical and sectoral characteristics. Although the current literature discusses WFH extensively (Barrero et al., 2023), it lacks such a rich set of soft and hard data.[2]

Second, we contribute to the literature on the persistence of WFH and its effects on firms' performance (Bloom, Liang, Roberts, and Ying, 2015; Barrero et al., 2021, 2023), by leveraging on hard data covering four years after the pandemic onset. We show that persistence is at most incomplete, echoing findings by Barrero et al. (2023). We can assess both the contemporaneous and the post-pandemic effect of WFH on firm labour productivity thus advancing our understanding in addition to papers based on field experiments (Atkin, Schoar, and Shinde, 2023; Choudhury et al., 2024) or self-reported worker data (Burdett, Etheridge, Tang, and Wang, 2024). Our findings of non-negative impacts suggest that, on average, the pandemic allowed firms to learn about WFH without being harmed in terms labour productivity.[3] Moreover, the richness of our data allows us to explore the heterogeneity of WFH effects despite a relatively small sample size. Our findings are consistent with those of Juhasz, Squicciarini, and Voigtländer (2020), who emphasize the importance of firm-specific characteristics in the long-term adoption of WFH. While Juhasz et al. (2020) and Lamorgese et al. (2024) show that prior WFH experience and the ability to coordinate employees determine long-run persistence, we highlight the importance of experiencing non-negative effects on labour productivity in alleviating frictions to the adoption of WFH.[4]

Lastly, this paper explores firm-level employment dynamics, composition, and wage effects, complementing the limited worker-level evidence that is largely based on self-reported data or is limited to the pandemic period (Mas and Pallais, 2020; Barrero, Bloom, Davis, Meyer, and Mihaylov, 2022; Alipour, Falck, and Schüller, 2023; Pabilonia and Vernon, 2024; Hensvik, Le Barbanchon, and Rathelot, 2020; Adams-Prassl, Boneva, Golin, and Rauh, 2022; Aksoy, Barrero, Bloom, Davis, Dolls, and Zarate, 2023; Cullen, Pakzad-Hurson, and Perez-Truglia, 2025).

The paper is organized as follows. Section 2 presents descriptive results on WFH adoption and its determinants during and after the pandemic. Section 3 introduces the empirical model, discusses the identification strategy, and presents tests that validate it. Section 4 details the main regression results on firm-level outcomes while Section 5 presents the heterogeneity analysis. Finally, Section 6 concludes.

[2] Bergeaud, Cette, and Drapala (2023) and Bratti, Brunetti, Corvasce, Maida, and Ricci (2024) explore, respectively, French and Italian firms' survey and administrative data but focus exclusively on WFH effects during the Covid-19 pandemic.

[3] The result is in line with Boeri et al. (2025) in their analysis ending in 2022, while they find a negative effect in 2020, and with Burdett et al. (2024) who focus on workers' reported productivity up until 2021.

[4] In additional analyses, we show that digital technologies facilitate the realisation of WFH benefits. This result is consistent with Gathmann, Kagerl, Pohlan, and Roth (2024), who previously demonstrated that investments in digital technologies helped firms stabilize employment and reduce short-time work during the pandemic.

2 Working from home during and after the pandemic

2.1 Data

We compile data from various sources at the firm level. Our primary one is the Banca d'Italia's Survey of Industrial and Service Firms (INVIND), conducted annually since 1984 among firms employing 20 or more individuals. To gauge the extent of remote work, we rely on a key survey question that asks respondents to report the percentage of employees who worked from home on a daily basis from 2019 to 2023[5]

Additionally, the survey captures a range of firm characteristics, including industry sector, geographical location, and management practices based on the Management and Organizational Practice Survey (MOPS; Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten, and Van Reenen, 2019; Lamorgese et al., 2024). Moreover, it records investment decisions (such as investments in tangible and intangible assets, advanced technologies, and R&D expenditure) and economic performance metrics (e.g., revenues and exports). We utilize this information both to control for predetermined firm-level characteristics (averaged values between 2017 and 2019) and as outcome variables for the years 2020 to 2023.

We complement this dataset with two other sources. Firstly, we utilize the Italian Social Security Institute (INPS) employer-employee matched data to extract details on firm-level average earnings and employment composition (including the percentage of fixed-term contracts and the proportion of female employment). Secondly, we gather additional information on firms' revenues and costs from balance sheet data.

We construct two variables that determine the use of work-from-home arrangements from external data. First, from the Italian Labour Force Survey we construct how many jobs can be performed from home in each narrowly-defined sector solely based on their ex ante characteristics. Borrowing from Basso et al. (2022), we define such variable as the sectoral share of those professional figures whose duties can be carried out remotely because they do not require, for most time, in-person human interactions (with customers, patients, suppliers or co-workers). The definition, similar to the one developed by Dingel and Neiman (2020), is based on the job tasks described for each occupation by the U.S. Department of labour O*NET survey (properly matched to the Italian data through standard occupational and sectoral crosswalk). Second, we collect data on the speed of broadband internet offered in each Italian municipality in 2019, as measured by the Italian Communications Regulatory Authority (AGCOM, 2019). It is important to note that this measure reflects the technical capacity of the supply side and does not represent the realized outcome resulting from the interaction between internet demand and supply.

[5] The survey asked "What was the average share of staff working remotely on a given day in year y?" ($y = 2019, 2021, 2022, 2023$).

Our main sample, which covers all years from 2017 to 2023, consists of 1,563 firms for which we observe all the variables used in the analyses. To achieve representativeness of the population of industrial and service firms with at least 20 employees, we use the weights provided by the survey. In additional analyses, we extend the sample to up to 2,300 firms by relaxing the no-missing variable condition for all years. The main results (reported in Appendix 2) are substantially unchanged, although with lower power of the instrument. We also confirm that the balanced sample of firms used for the regression analysis and the more extended and unbalanced sample do not systematically differ in terms of observables.

2.2 Descriptive statistics about WFH

Work from home arrangements were uncommon in Italy before the pandemic. According to our data, just 9.8% of firms reported using it in 2019, and on average the percentage of workers using it every day was 1.2 overall (the extensive and intensive margin over time are reported in Figure 1).[6] The pandemic induced a sudden increase in WFH arrangements. Our data indicate that 58.6% of firms reported using it in 2020, a 49 percentage point jump in just one year.[7] As described in a policy brief by Basso and Formai (2021), this increase was widespread across industries, regions, and firms' size and age classes. However, there is substantial variability in the intensity of WFH use between firms: in 2020, it spans from zero to up to 50% of the workforce in the 90th percentile of the distribution.

Despite the decline in the use of WFH after 2020, 39% of firms still reported using at least some of it in 2021, 28% of firms in 2023, about half of the incidence in 2020 (Figure 1a). The average intensive margin dropped by 10 percentage points, stabilizing to around 4.5% (Figure 1b).

Although WFH went through a period of normalization after the pandemic boom, adoption by many firms was a permanent choice. The persistence of WFH working arrangements is shown in Figure 2. Panel 2a reports the change in the intensive margin between 2019 and 2020 (on the x-axis) to that between 2019 and 2021 (on the y-axis). The correlation falls below the 45 degree line, but is substantial (0.7). Despite the further drop in 2022, the persistence between 2021 and 2023 remains high (0.5; panel 2b).[8]

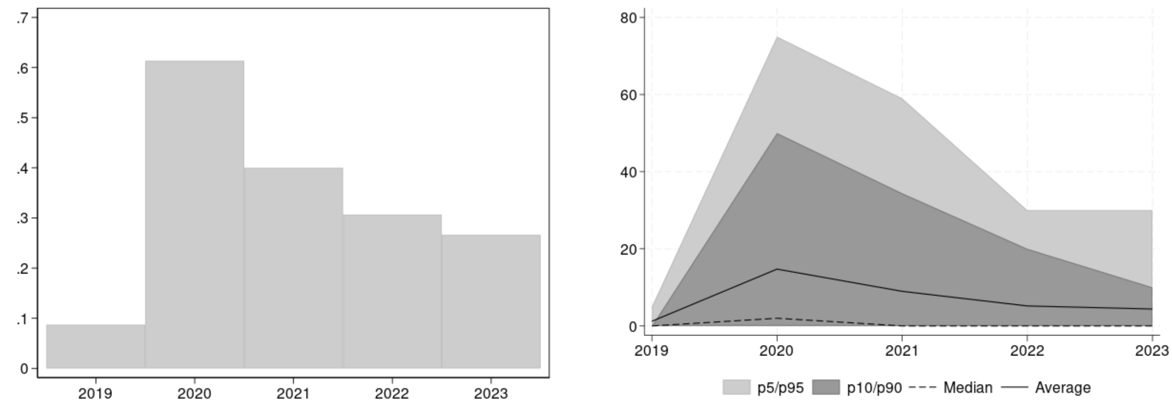
The aggregate figures described so far hide a strong degree of heterogeneity depending

[6]When excluding firms that do not implement WFH at all, the percentage of workers using it every is on average 11.4 in 2019 and 24.0 in 2020.

[7]A companion Banca d'Italia survey run in Italy in September 2020, before the second pandemic wave, indicates an even higher jump in the use of WFH in the first nine months of 2020. Furthermore, according to administrative data from the Ministry of Labour data reported in Crescenzi, Giua, and Rigo (2022), the number of workers reported working from home increased from less than 200,000 at the end of 2019 to more than 1.5 million in early March 2020.

[8]In the Appendix we report persistence from regressions of the changes in the use of WFH controlling for the pre-pandemic firm characteristics that are included in the rest of the analysis: persistence remains high (Table 1.1).

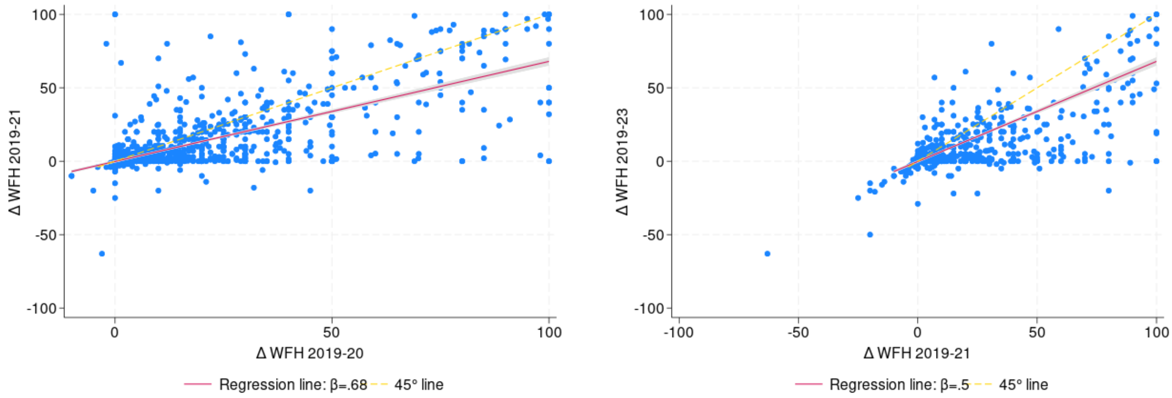
Figure 1: The use of WFH, 2019-2023



(a) Extensive margin (b) Intensive margin

Notes: Elaborations on INVIND data. The graph shows the extensive margin of the use of WFH (panel a), measured as share of firms, and its intensive margin distribution, measured as percentage of firm's employees (panel b), over time for the sample firms that enter the balanced dataset on which we base the analysis in the following sections (i.e., 1563 firms).

Figure 2: Persistence in the use of WFH



(a) 2020-2021 (b) 2023-2021

Notes: Elaborations on INVIND data. Panel (a) plots the change in the share of firm's workers using WFH between 2019 and 2020 (x-axis) and between 2019 and 2021 (y-axis). Panel (b) plots the change in the same variable computed between 2021 and 2019 (x-axis) and between 2023 and 2019 (y-axis). The regression lines report an unconditional correlation between the two quantities. The sample comprises the firms that enter the balanced panel on which we base the analysis in the following sections (i.e., 1563 firms).

on firms characteristics. Leaving aside the emergency induced by the first pandemic wave, Table 1 reports for 2021 (columns 1 and 2) and 2023 (columns 3 and 4) the average extensive and intensive margins of adoption for different groups of firms, conditional on all the other demographic characteristics in the table. In 2023 WFH was extensively adopted in all four main geographic areas, but much more so in the North of the country (1 out of 3 firms, against 1 out of 5 in the Center-South), even after controlling for the sectoral specialization. The drop with respect to 2021 was more pronounced in the North East and in the Center. The adoption of WFH varies substantially across sectors, especially in 2023, when up to 74% of firms in IT services and 65% in professional activities reported using WFH, compared to just 6% in accommodation and food services. Intensive margin shares largely reflect the extensive margin figures but indicate that even sectors where WFH is harder to adopt for the wide workforce, it was used, possibly in supporting/office activities (e.g., 30% of firms in trade sectors reported having at least some workers WFH). In terms of firms' size, larger companies were more likely not only to adopt some WFH but also to use it more intensively. Patterns in terms of firms' age have changed over time: in 2023, younger firms were more likely to use it than older firms. Finally, firms belonging to foreign groups use WFH arrangements both more extensively and intensively than other firms in both years.

2.3 Firm-level determinants of WFH adoption

Besides the heterogeneity across demographics, other firms' characteristics may facilitate the adoption of WFH. Even within sectors, firms differ greatly in terms of productivity, investments in telecommunication and information technologies, and managerial practices. Tables 2 and 3 report the results of simple OLS regressions aimed at characterizing the main determinants of the use of WFH at the firm level, controlling for the main characteristics of the firm reported in Table 1 (i.e. size, age, geographic location and business sector). All the variables are measured as 2017-2019 averages, unless reported otherwise.

Regarding the extensive margin in the use of WFH (column (1) and (3)), a higher share of workers who can potentially work from home in a narrowly defined sector, as measured by Basso et al. (2022), the adoption of cloud technologies, a higher share of female workers, higher wages and higher expenditures in research and development (R&D) increase the probability of using WFH in both 2021 and 2023. The intensive margin (columns (2) and (4)) correlates positively with wages, productivity and female employment.

Table 3 tests the hypothesis that more structured managerial practices, based on monitoring, target settings and incentives, might ease WFH adoption (Bloom, Sadun, and Van Reenen, 2012). In 2020 a small sample of firms were asked about structured managerial practices in the INVIND survey and for them is possible to construct a standardized MOPS indicator (Bloom

Table 1: Firm demographics and WFH - Conditional means 2021 and 2023.

	2021		2023	
	Ext. margin	Int. margin	Ext. margin	Int. margin
North West	42.7	9.9	32.7	5.2
North East	44.3	7.1	29.1	3.5
Center	33.1	9.5	20.5	4.9
South/Islands	29.6	7.4	19.9	3.4
Size < 25	35.8	11.0	18.9	5.7
Size 25-49	31.7	6.5	22.2	2.9
Size 50-249	49.2	10.7	32.0	5.8
Size > 50	54.7	11.6	39.4	7.7
Age 1-6	30.3	4.0	34.2	3.6
Age 7-11	56.2	14.7	38.3	8.4
Age 12-20	43.4	8.9	30.1	5.1
Age > 20	37.8	8.4	24.4	4.1
Accomodation and food serv.	35.9	3.7	6.1	0.8
Administr. and support serv.	44.5	13.2	40.6	9.4
Electricity, gas	49.7	20.1	34.2	8.5
Inform. and comm.	72.2	47.6	73.8	33.5
Manufacturing	32.1	4.4	19.6	2.0
Professional activities	74.6	23.3	65.4	9.4
Transport. and storage	33.9	6.2	18.5	2.2
Water and waste	54.3	7.7	29.6	1.8
Wholesales and retail trade	37.1	7.7	29.6	1.8
No group	31.1	5.9	20.3	3.0
Italian group	53.1	12.1	34.0	4.7
Foreign group	71.5	23.5	52.3	16.6
N	1563	1563	1563	1563

Notes: Conditional mean on other covariates for each group. The size class is defined in terms of average number of employees between 2017 and 2019, the age class in terms of the age of the firm in 2019. The last three rows refer to firms that in 2029 do not belong to any group, those that belong to a group with and Italian parent firm and those that belong to a foreign group respectively.

Table 2: Firm characteristics and WFH - 2021 and 2023.

	2021		2023	
	Ext. marg.	Int. marg.	Ext. marg.	Int. marg.
Proxy WFH-able	0.563**	11.131	0.368*	2.195
	(0.169)	(6.998)	(0.147)	(4.253)
Cloud comput. adoption	0.065^{+}	1.483	0.077*	1.046
	(0.038)	(1.246)	(0.034)	(0.855)
Sh.fixed term	-0.253	-12.701**	-0.262*	-5.733
	(0.201)	(4.057)	(0.116)	(3.780)
Sh.female	0.392**	19.793**	0.397**	11.318**
	(0.095)	(4.268)	(0.092)	(2.682)
log(wage)	0.144**	6.430**	0.121**	5.352**
	(0.046)	(1.626)	(0.033)	(1.139)
log(prod)	0.029	2.033**	0.019	0.843^{+}
	(0.024)	(0.761)	(0.017)	(0.480)
Sh. export	0.150*	-0.968	-0.061	-2.083
	(0.069)	(2.210)	(0.052)	(1.534)
R&D	0.014^{+}	2.663**	0.022*	0.084
	(0.008)	(0.312)	(0.010)	(0.195)
N	1563	1563	1563	1563
R^2	0.445	0.579	0.449	0.557

Notes: Proxy WFH is defined according to Basso, Boeri, Caiumi, and Paccagnella (2020). Cloud adoption is a dummy equals to 1 if the firm has invested in could technologies between 2017 and 2019. All other variables are computed as 2017-2019 averages. Sh. fixed term and Sh. female are computed as the share of fixed term contracts and female employees on total employment, respectively. Sh. export and R&D are defined respectively as the share of export revenues and R&D investments on total revenues. All regressions include industry, size class and macro area fixed effects. Heteroskedasticity-robust standard errors. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

and Van Reenen, 2007; Lamorgese et al., 2024).[9] The results of the regression indicate that a one standard deviation higher MOPS before the pandemic is correlated with a 5 percentage point increase in the probability of adopting WFH and a 1.3 percentage point higher share of workers using it in 2021. The effect on the extensive margin halves in 2023.[10]

Table 3: Management practices and WFH.

	2021		2023	
	Ext. margin	Int. margin	Ext. margin	Int. margin
MOPS (Z-score)	0.048*	1.307*	0.026^{+}	1.319*
	(0.020)	(0.649)	(0.016)	(0.545)
N	910	910	910	910
R^2	0.457	0.657	0.457	0.663

Notes: The MOPS variable has been collected with the INVIND 2020 wave and explicitly refers to management practices in place in 2019. All regressions include industry, size class and macro area fixed effects, in addition to all variables in Table 2. Heteroskedasticity-robust standard errors in parentheses. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

3 Empirical model and identification strategy

3.1 The empirical model

We want to determine whether the use of WFH following the pandemic shock affected firms' outcomes. We consider the following econometric specification, focusing on the period 2019-2023 (medium-run; mr):

$$\Delta_{19-23} \log y_i = \alpha^{mr} + \beta^{mr} \Delta_{19-21} WFH_i + X'_{i,2019} \gamma^{mr} + \epsilon_i \quad (1)$$

where $\Delta_{t_0 - t_1}$ represents the difference operator over the period t_0 and t_1; $\Delta_{19-21} WFH_i$ is the change in the share of staff working remotely at the survey's reference date between 2019 and 2021. This means that β includes both the direct channel (going through the effect of WFH during the pandemic) and the indirect one (going through subsequent adoption of WFH). The main outcome variable y_i is labour productivity, defined as revenues (or real output) over labour input (measured as headcounts or hours).[11] In addition, we consider revenues (quantities), total

[9] The survey questions that contribute to the construction of the standardized MOPS indicator are based on a survey developed and administered by the US Census Bureau. They aim to asses how activity is monitored, how targets for production and other monitored performance indicators are set and how achievement of those targets is incentivized (see the Management and Organizational Practices Survey webpage). For more info on the INVIND survey and the Italian MOPS indicator see Lamorgese et al. (2024).

[10] The regressions in Table 3 include all the control variables reported in Tables 1 and 2.

[11] Real output is measured as revenues divided by the firm-level price index with base year 2019, as obtained from the INVIND survey.

hours worked, and employment as separate outcomes, in order to detect the effect on each component of labour productivity.

The vector $X_{i,2019}$ contains various characteristics of the firm observed before the pandemic (in 2019 or as averages for 2017-2019). These variables are included taking into account the evidence shown in Tables 1 and 2 about the determinants of WFH adoption. More in details, $X_{i,2019}$ includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector.[12] In all regressions, we cluster the standard errors at the province-by-sector level to account for serial correlation at a more aggregate cluster than that of our identifying variation (Cameron and Miller, 2015).

The coefficient of interest is β, capturing the impact of the shift in the firm's use of WFH. However, establishing a causal nexus is complicated by the endogenous take-up of WFH. Although our dataset is very rich in terms of firm characteristics that are associated with the adoption of WFH, as shown in the previous section, there may still be some unobservable variables that are correlated with both the firms' decision to adopt WFH arrangements and labour productivity. Moreover, an OLS estimation may suffer from reverse causality, especially in equation (2), because concurrent changes in productivity can have an impact on the firm's decision about using WFH. In what follows, we propose an IV identification strategy that relies on plausibly exogenous variation in the use of WFH.

In additional analyses, reported in the Appendix, we also assess the short-run effect of WFH adoption during the pandemic focusing on the period 2019-2021.[13]

3.2 The instrumental variable

To instrument the change in the use of WFH, we leverage the predetermined variation in the interaction between: (i) the speed of broadband internet connection in the commuting zone (CZ) where the firm is located, and (ii) the share of jobs that are potentially workable from home in a narrowly-defined industrial sector. In exploiting the interaction of these two dimensions as an instrument, we add both of them to the set of control variables. Hence, identification only comes from the interaction. As discussed below, this arguably increases the reliability

[12]The sector fixed-effect are at NACE rev. 2 one-digit but for manufacturing, where two-digit subgroups are considered thanks to the higher number of observations.

[13] We run the model:

$$\Delta_{19-21} \log y_i = \alpha + \beta \Delta_{19-21} WFH_i + X'_{i,2019}\gamma + \varepsilon_{it} \tag{2}$$

where the variables are defined as in equation (1). All results are substantially confirmed also for the shorter period 2019-2020. They are available from the authors upon request.

of the exclusion restriction: the WFH potential at the sectoral level could include some other sector-specific factors that might be correlated with the outcome; similarly, the speed of the broadband connection in the area could affect the productivity of the firm through channels other than WFH. By controlling for both these factors taken separately, we argue that their interaction matters for our outcomes of interest only through the actual use of WFH, by acting as an enabling exogenous determinant, i.e. both potential and broadband speed are relevant to make WFH feasible and effective.

The first element of the interaction term is measured as the average speed in the CZ in 2019, before the pandemic, as reported by the Italian Communications Regulatory Authority. We take as unit of geography the CZ as both the firm (where most likely the servers are located) and the workers need to have a good internet connection for work from home arrangements.[14]

The second term, the WFH potential, aims at capturing the share of the workforce that could potentially work from home at the onset of the pandemic based on the task-based definition of Basso et al. (2022).[15] Under this classification, which follows that of Dingel and Neiman (2020), occupations whose tasks can be performed from home are those that require no in person interactions with customers, coworkers or suppliers, as measured in the Bureau of labour Statistics O*Net database (for further details see Basso et al., 2022). We rely on the 2019 occupation composition at the NACE rev. 2 three-digit average, thereby avoiding any potential endogeneity in the share of jobs workable from home at the firm level.

The aim of the interaction-based instrument is to exploit the variation in a WFH determinant that is not under direct control of the firm at the onset of the pandemic. Importantly, the interaction term is predetermined when the Covid-19 shock unexpectedly occurred in February 2020, making the transition to WFH easier for some firms and more difficult for others. The pandemic shock was indeed unanticipated, and the combination of broadband speed and WFH potential acted as an exogenous factor that firms could not manipulate in the short run. In the longer run, as firms have adapted, the use of WFH may have become increasingly dependent on several other —often unobserved— endogenous determinants, making our instrument presumably weaker in predicting the actual use of WFH. This is indeed what we find in the analysis on the relevance of our instrument (see Section 3.3). Hence, our IV strategy aims at estimating a local average treatment effect (LATE) of the change in firm productivity due to the heterogeneous shift in WFH induced by the unanticipated pandemic shock and given firm's exogenous readiness to work in remote, both in the short and in the medium run.

[14]In case of multi-plant firms, the broadband speed is that of the firm headquarter.

[15]The results are robust to alternative definitions, including the one developed specifically on Italian data by Barbieri, Basso, and Scicchitano (2022).

3.3 The identification assumptions

The identification of the causal effects by our IV strategy is ensured under four assumptions. More specifically:

A1. Relevance: It requires that the instrument has predictive power in explaining the change in WFH, once the same set of control variables used in the main regression is accounted for. We test this assumption by means of a first-stage regression where the dependent variable is the WFH change between 2019 and each year from 2020 to 2023. The sample of firms available for OLS estimates of model (2) in each and every ending year from 2020 to 2023 is considered, thus ensuring a balanced number of firms.[16] The explanatory variable of interest is the IV, i.e.: the interaction between the (predetermined) industry-level WFH potential and the (predetermined) CZ-average broadband speed. Since we include both these variables among the controls, the assumption of relevance requires that their interaction matters on top of the effect that each variable has *per se*.

Table 4: First-stage regressions

	(1) Δ_{19-20} WFH	(2) Δ_{19-21} WFH	(3) Δ_{19-22} WFH	(4) Δ_{19-23} WFH
Av.bb speed*Proxy WFH-able	0.151**	0.121**	0.067*	0.055*
	(0.031)	(0.030)	(0.032)	(0.028)
OP F-stat	23.7	15.7	4.5	3.9
N	1563	1563	1563	1563
R^2	0.52	0.46	0.34	0.34

Notes: Average broadband (Av.bb) speed measures the average broadband speed at the municipality level. The share of WFH-able workers (Proxy WFH-able) is measured at the 3-digit sectoral level. All regressions are weighted using INVIND survey weights. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

As shown in Table 4, the instrument has a strongly significant coefficient for the WFH change until 2021, whereas the relationship is weaker in later years. Also the robust F-test statistic is above conventional levels for instrument power in the first two columns, while it takes low values for the changes up to 2022 and 2023. This is consistent with our prior, as the IV was supposedly more strongly related to short-run changes in the use of WFH, while other factors could have become more relevant over time as firms have had time to adjust. Up to 2021, the actual use of WFH following the pandemic shock appears to be significantly determined by the joint combination of WFH potential at the industry level and the broadband speed in the local area.

[16]In what follows, we keep this estimation sample, while in the Appendix 2 we consider a larger (but unbalanced) sample, showing that results are confirmed, though with a lower power of the instrument. Moreover, we test and confirm that, based on observables, the balanced sample of firm we used for the regression analysis do not significantly differ from the more extended sample.

Based on the evidence in Table 4, we analyse the effect over the medium run through the model in equation (1). Moreover, in order to mitigate any further concern about possible instrument's weakness, in the rest of the analyses we also report Anderson-Rubin confidence sets. By relying on partial identification, weaker assumptions are needed, in particular with regard to the strength of the instrument (Andrews et al., 2019).

A2. Independence/parallel trends: It requires that the interaction between the sectoral composition of the workforce and the local availability of high-speed broadband is not predictive of average changes in firm productivity that would have occurred absent the Covid-19 shock. This assumption would be violated if firms anticipating a change in productivity in the forthcoming year ahead adjusted their workforce composition in advance (i.e., prior to early 2020) or relocated to a better-connected municipality.

In order to mitigate this kind of worries, we recall that we fix the share of the workforce whose occupational tasks can be performed from remote at the sectoral level, thereby ensuring that the firm-specific workforce composition is not the main driver. Moreover, we provide pre-trend tests showing that firms that were potentially WFH-ready: (i) were not on a growing or shrinking trend in terms of labour productivity (nor with respect to revenues or employment) in the years before the Covid-19 pandemic (Table 5);[17] (ii) did not change the workforce composition before the pandemic in a way statistically different from other firms (Table 6, columns 1-4); (iii) did not change location in the years preceding the Covid-19 shock to take advantage of the broadband availability (Table 6, column 5). All the results confirm that, in the period preceding 2020, firms did not show differences in labour productivity, in its main components and in the composition of the workforce, nor they did systematically change location as a function of the instrument.

Table 5: Pre-trends in outcome variables

	(1) $\Delta_{17-19}\log(\frac{rev.}{empl.})$	(2) $\Delta_{17-19}\log(\frac{rev.}{hours})$	(3) $\Delta_{17-19}\log(rev.)$	(4) $\Delta_{17-19}\log(empl.)$	(5) $\Delta_{17-19}\log(hours)$
Av.bb speed*Proxy WFH-able	-0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	1563	1563	1563	1563	1563
R^2	0.112	0.102	0.165	0.137	0.119

Notes: All regressions are weighted using INVIND survey weights. The dependent variable refers to: in col. (1), labour productivity in terms of revenues and headcounts; in col. (2), labour productivity in terms of revenues and hours worked; in col. (3) revenues; in col. (4), labour headcounts; in col. (5) hours worked. Non-significant results are also found when volumes are considered instead of revenues (available upon request). Average broadband (Av.bb) speed measures the average broadband speed at the municipality level. The share of WFH-able workers (Proxy WFH-able) is measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

The early adoption of WFH in 2020 was associated with several firm-specific factors, as we saw in Section 2.3. Thus, we want to test that the IV has independent predictive power. Once

[17]Table 5 clearly shows no statistical significance. As the coefficients and standard errors are equal to zero up to the third decimal place due to scaling reasons, we further verify that the effect implied by the coefficient's point estimate multiplied by a one-standard deviation increase in the instrument represents only a limited fraction of the standard deviation of the dependent variable.

Table 6: Test for pre-pandemic changes in work force composition and municipality

	(1) Δ_{17-19}Sh.managers	(2) Δ_{17-19}Sh.blue-collars	(3) Δ_{17-19}Sh. female	(4) Δ_{17-19}Sh.young	(5) change munic.
Av.bb speed*Proxy WFH-able	0.000	-0.000	0.002	-0.000	-0.000
	(0.000)	(0.000)	(0.020)	(0.000)	(0.001)
N	1563	1563	1561	1561	1563
R^2	0.084	0.112	0.023	0.184	0.100

Notes: All regressions are weighted using INVIND survey weights. The dependent variable refers to: in col. (1), share of managers out of total employees; in col. (2), share of blue-collar workers out ot total employees; in col. (3), share of female employees; in col. (4), share of workers aged between 15 and 34 years old; in col. (5) a dummy indicating whether firm changed its location to another municipality in the 2017-2019 period. Average broadband (Av.bb) speed measures the average broadband speed at the municipality level. The share of WFH-able workers (Proxy WFH-able) is measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

we control for WFH potential and broadband speed, the instrument is indeed uncorrelated with most of the covariates, with the exception of the share of temporary workers and for the joint test on all sector-area fixed effects (see Table 1.3 in the Appendix). Since we control for these variables in all regressions, as well as for all other WFH determinants, we are confident on the conditional validity of the instrument.

A3. Exclusion restriction: It requires that the instrument has no predictive power on the average change in productivity, once we condition on the change in the use of remote working. In other terms, the instrument impacts the average change in productivity only through WFH, conditionally on the control variables. To this end, recall that we also control for the two IV components taken individually in order to control for any direct effect from each of them. First, WFH potential could be correlated with some industry-specific factors potentially correlated in turn with the dependent variable. Second, the average local broadband speed could be associated with a positive effect on productivity via better infrastructures, workforce composition and technology-skill complementarity (Akerman, Gaarder, and Mogstad, 2015; Ciapanna and Colonna, 2019).

Moreover, the exclusion restriction could be violated if the instrument correlates with other firm-level shocks that occurred in the same period. We check that this is not the case for the main macroeconomic shock that characterized the post-pandemic recovery: labour supply shortages; the energy crisis; the global value chain bottlenecks in 2021 affecting, in particular, the supply of semiconductor. Results reported in Table 7 are somewhat reassuring about the exclusion-restriction assumption.[18]

A4. Monotonicity: It requires that the instrument has either a non-negative or a non-positive impact on the endogenous variable for all firms. In our context, it requires that the effect of the interaction between WFH potential and broadband speed is non-negative for all firms. This further implies that the actual use of WFH is positively related to the instrument, at both low and high values of the instrument. Consequently, we should observe that the actual use of WFH is more pronounced at higher levels of the instrument. Such assumption would be invalidated,

[18]In the last column, the sample size declines because of the lower number of respondents to that specific question.

Table 7: Correlation between IV and other macroeconomic shocks occurred between 2019 and 2021

	(1) Labour Supply	(2) Energy Prices	(3) Semiconductor Supply
Av.bb speed*Proxy WFH-able	0.001	-0.000	0.002
	(0.001)	(0.001)	(0.002)
N	1474	1496	745
R^2	0.171	0.137	0.259

Notes: All regressions are weighted using INVIND survey weights. The dependent variable is a dummy indicating firms that reported: in col. (1), difficulties due to labour-supply shortages; in col. (2), difficulties due to soaring energy prices; in col. (3), difficulties due to bottlenecks in the supply of semiconductors. Average broadband (Av.bb) speed measures the average broadband speed at the municipality level. The share of WFH-able workers (Proxy WFH-able) is measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

for instance, if there were firms such that the joint occurrence of a large share of workers who can work from home and the availability of high-speed internet would induce a lower adoption of WFH when the pandemic hit. Such instance seems unlikely.

Following Angrist and Imbens (1995) and Angrist, Graddy, and Imbens (2000), we provide evidence in support of this assumption by reporting the cumulative distribution function of WFH use depending on the value of the instrument (which we split in four groups according to its quartiles). As can be seen in Figure 3, the distribution for the firms with a better combination of broadband and workforce share that can work remotely first-order stochastically dominates the distribution of firms with lower values of the IV. This is a necessary condition for monotonicity to hold. Should the distributions intersect, it would be implied that the effect of the instrument is positive for some units and negative for others, thus violating the assumption of monotonicity.

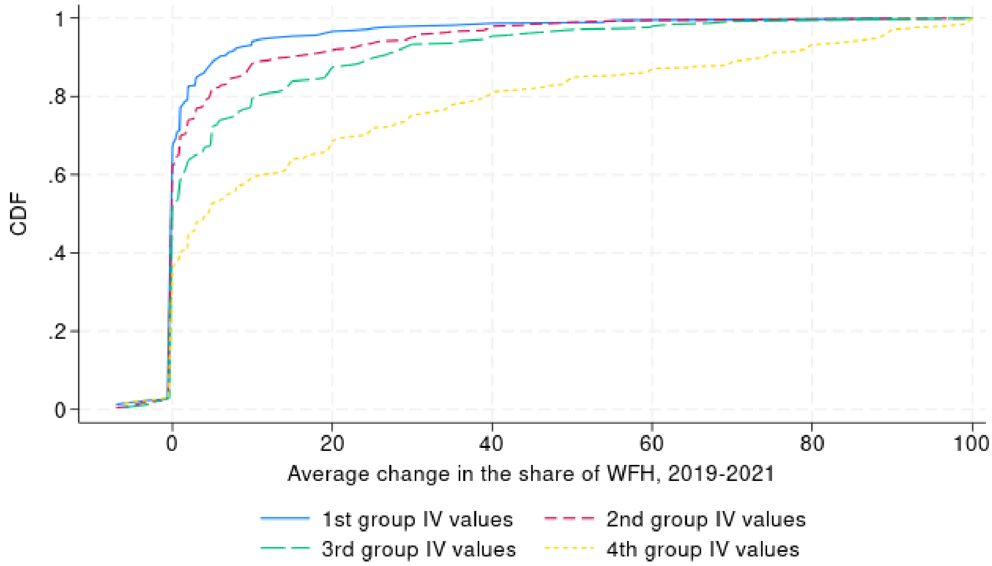
Aside from testing for monotonicity, Figure 3 provides a very transparent representation of the variation that is captured by our IV and used to identify the effects. The horizontal difference between the curves is directly related to the relevance of the IV. As a consequence, the plot illustrates what segments of the remote work usage change distribution are more influenced by the instrument. This is a useful piece of information for the interpretation of the instrument.

4 Main results

We present here the results for the medium-run model in equation (1). We report the estimates for the short-run model —as described in equation (2), footnote 13— in the Appendix.

Table 8 shows that the pandemic-induced shift towards remote working neither hindered

Figure 3: Monotonocity of the IV



Notes: Elaborations on INVIND data. The graph reports the cumulative distribution function of the change in WFH use between 2019 and 2021 separately for firms belonging to different groups defined by the quartiles of the IV distribution.

nor improved firms' productivity in medium rum.[19] The null result holds irrespectively of how productivity is measured (nominal or real value) and whether it is taken with respect to workers' headcounts or hours. This also mitigates concerns that hours worked at home could be misreported in a systematic way (we further discuss issues related to measurement error in hours worked in Section 5). This suggests that on average there were neither productivity losses nor gains from having used more WFH during and after the pandemic. If any, the two-stage-least-square coefficients are positive, though not statistically significant. Moreover, AR-bounds tend to lie more on the positive side indicating productivity changes between -0.7% and 1.0%.

We can also observe that the OLS coefficients in Table 8 are negative and significant. For all the reasons described in Section 3, these coefficients presumably do not capture a causal relationship and are affected by endogeneity issues. As our IV strategy limits the role of firm-specific factors, it is likely that the bias of the OLS estimator corrected by the 2SLS estimator is related to them.

In order to investigate this issue further and to inspect our results more in depth, now we consider the numerator —firm performance (in revenues or volumes)— and the denominator —labour input (hours or headcounts)— of productivity as separate outcomes. The null effect of WFH on productivity may indeed be due to either the absence of any effect at all on both

[19]Table 3.1 in the Appendix reports that the same occurred in the short run as well.

Table 8: WFH and labour productivity: Medium run

	(1) $\Delta_{19-23}\log(\frac{revenues}{hours})$	(2) $\Delta_{19-23}\log(\frac{revenues}{employm.})$	(3) $\Delta_{19-23}\log(\frac{volumes}{hours})$	(4) $\Delta_{19-23}\log(\frac{volumes}{employm.})$
Panel a. OLS				
Δ_{19-21} WFH	-0.002**	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Panel b. 2SLS				
Δ_{19-21} WFH	0.001	0.003	0.001	0.003
	(0.004)	(0.003)	(0.004)	(0.003)
AR bounds	[-0.007, 0.010]	[-0.004, 0.012]	[-0.008, 0.010]	[-0.003, 0.012]
OP F-stat	15.7	15.7	15.7	15.7
N	1563	1563	1563	1563
Pre-2020 avg. outcome	0.293	484.1	0.507	831.6

Notes: All regressions are weighted using INVIND survey weights. Outcomes are in nominal terms in the first two columns and in real terms in the last two columns. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

the numerator and the denominator, or it may result from effects in the same direction that countervail each other.

As shown in the top panel of Table 9, the negative correlation between WFH and productivity resulting from the OLS estimates operates through labour input (the denominator of productivity): firms that used WFH more also increased more (or decreased less) their labour input. Taking into account that the descriptive evidence in Section 2 hints to some positive selection in WFH adoption, it is possible that firms that (endogenously) used more WFH also implemented some labour-hoarding foreseeing possible shortages or were better able to keep their workers even in a turmoil period. Hence, these firms showed better employment dynamics, while the growth in revenues or volumes was similar. For these firms, WFH could have also been a tool to attract or keep workers in a period where the workers' interest on this scheme considerably increased. Anyway, getting rid of such firm-specific endogenous factors is exactly the aim of our IV approach: the 2SLS estimates shown in the bottom panel of Table 9 point to a null effect of WFH adoption on labour productivity when such endogenous confounders are netted out.[20]

Though the use of WFH did not significantly impact the employment dynamics overall, it could affect the employment mix, especially with respect to gender composition, age-structure (percentage of workers below 35 years of age) and skill-mix (proxied by broad occupational types: white-collars, blue-collars and managers).[21]

[20] The corresponding results for the short-run model can be found in Table 3.2 in the Appendix.

[21] Since these changes may take some time to become apparent, we keep our focus on the medium-term model,

Table 9: WFH, firm performance and labour: Medium run

	(1) $\Delta_{19-23}\log(revenues)$	(2) $\Delta_{19-23}\log(volumes)$	(3) $\Delta_{19-23}\log(hours)$	(4) $\Delta_{19-23}\log(employm.)$
Panel a. OLS				
Δ_{19-21} WFH	-0.001	-0.001	0.001+	0.001+
	(0.001)	(0.001)	(0.001)	(0.000)
Panel b. 2SLS				
Δ_{19-21} WFH	0.002	0.002	0.001	-0.001
	(0.004)	(0.004)	(0.003)	(0.002)
AR bounds	[-0.007, 0.011]	[-0.007, 0.011]	[-0.006, 0.008]	[-0.008, 0.004]
OP F-stat	15.7	15.7	15.7	15.7
N	1563	1563	1563	1563
Pre-2020 avg. outcome	191.4	342.3	740.4	486

Notes: All regressions are weighted using INVIND survey weights. The pre-2020 avg. otucomes in columns (1), (2) are in millions of euro, in column (3) in thousands of hours. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

However, Table 10 shows that there was no significant impact from WFH on the employment mix at the firm level at least until 2022.[22] In all the regressions, the estimates are precisely zeros and the AR-bounds are well within one percentage point around zero.[23]

We also assess whether WFH has had any effect on workers' compensation measured by average gross hourly, or monthly, wages. The effects are highly ambiguous ex ante, as a change in wages associated to the adoption of WFH could be due to a change in workforce composition (possibly not captured by the variables analysed in Tables 10), changes in productivity (although this channel is unlikely given the results presented so far) or because of compensating differentials —negative if WFH is perceived as a job amenity by the worker (Cullen et al., 2025), while positive if certain workers cannot actually work from home.

The first two columns of Table 11 show that, on average, wages were not significantly affected by the shift toward WFH. However, when we separately consider white collars and blue-collars, we find a negative sign, albeit not statistically significant, for white-collars and a positive and mildly significant effect on blue-collars.[24] These results should be taken with cau-

while continuing to report the short-run model in Appendix 3.

[22]Due to a lag in the availability of the data on the firm-level employment composition, the medium run analysis for these outcomes has to stop in 2022.

[23]Table 3.3 in the Appendix confirms this piece of evidence also for the short-run period.

[24]In this analysis white-collars do not include managers. The effect on managers is not explicitly assessed as the number of observations for managers is significantly lower and we would not observe managers' compensation in too many firms. Due to data availability on workers' compensation, the analysis of the medium run ends at 2022 as it is the most recent year for which data are available. These findings hold in the short-run model as well (Table 3.4 in the Appendix).

Table 10: WFH and employment mix: Medium run

	(1) Δ_{19-22} Sh.managers	(2) Δ_{19-22} Sh.white-collars	(3) Δ_{19-22} Sh.female	(4) Δ_{19-22} Sh.young
Panel a. OLS				
Δ_{19-21} WFH	0.000	-0.000	-0.000+	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel b. 2SLS				
Δ_{19-21} WFH	-0.000	0.001	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
AR bounds	[-0.001, 0.001]	[-0.001, 0.003]	[-0.002, 0.001]	[-0.004, 0.001]
OP F-stat	15.7	15.7	15.7	15.7
N	1563	1563	1563	1563
Pre-2020 avg. outcome	1.3%	38.8%	26.0%	18.0%

Notes: All regressions are weighted using INVIND survey weights. The dependent variable is the employment share of: in col. (1) managers, in col. (2) white-collar non-manager employees; in col. (3) female; in col. (4) employees aged 15 to 34 years old. The last year of analysis is 2022 due to a lag in the availability of data on employment composition. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

tion as in column (4) both the number of observations is lower and the IV power is weaker.[25] Still, these findings would be consistent with WFH being a job amenity for white-collar workers, while compensating differentials are needed for those workers who have little possibility to do it, such as the blue-collars because of their tasks must be performed mainly on site. Interestingly, if we run the regression on the sample for which we observe both white-collar and blue-collar workers and take as outcome the relative wage of white collars with respect to blue collars, we find a negative effect suggesting that the positive impact on blue collars' wage also holds in relative terms at the firm level.

Finally, we address another concern about the increased use of WFH, i.e. that it may have hindered firms' ability to innovate or affected their operating costs. At the same time, firms that adopt WFH massively need to invest in IT capital. In order to study these issues, we consider the firm investments in 4.0 technologies (defined as digital and automation technologies) and the change in firm's variable costs from balance sheet data.[26] Table 1.4 in the Appendix shows that the average effects are null on both these dimensions.

[25]This occurs because there are firms where blue-collar workers are not present (as well as there are firms without white-collar employees, though this is rarer in our sample).

[26]As regards 4.0 technology investments, we consider two variables: the highest class of investment incidence over yearly revenues between 2020 and 2023 and a dummy equal to 1 if in a at least one of those years an investment was made.

Table 11: WFH and workers' compensation: Medium run

	(1) $\Delta_{19-22}\log(hourly\,wage)$ all employees	(2) $\Delta_{19-22}\log(monthly\,w)$ all employees	(3) $\Delta_{19-22}\log(monthly\,w)$ white-collars	(4) $\Delta_{19-22}\log(monthly\,w)$ blue-collars
Panel a. OLS				
Δ_{19-21} WFH	-0.001	0.000	0.000	-0.001
	(0.001)	(0.000)	(0.001)	(0.001)
Panel b. 2SLS				
Δ_{19-21} WFH	0.001	0.002	-0.000	0.011+
	(0.004)	(0.003)	(0.003)	(0.006)
AR bounds	[-0.008, 0.012]	[-0.004, 0.010]	[-0.006, 0.006]	[0.002, 0.047]
OP F-stat	15.7	15.7	15.7	6.5
N	1563	1563	1558	1445
Pre-2020 avg. outcome	321.7	4052	4717	2878

Notes: All regressions are weighted using INVIND survey weights. Column (3) does not include managers among white-collars. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

5 Heterogeneity in the impact and persistence of WFH

5.1 Heterogeneous effects on labour productivity

Our findings of a precise zero effect of WFH on labour productivity and related outcomes holds on average. In this Section we tackle the issue that the impact can be not necessarily zero for all firms as they are heterogeneous.

First of all, we ascertain that the impact does not systematically depend on firm's size or sector, as shown in Table 1.5 and Table 1.6 in the Appendix, based on a sample-split approach.[27] If any, we find a positive impact of WFH on productivity for firms that, prior the pandemic, had invested at least 5% of their yearly revenues in digital and automation technologies (Table 1.7).[28] Being already equipped with up-todate IT technologies, these firms were able to take advantage of the WFH opportunities by improving their labour productivity in the medium run. Interestingly, the results also detect a slight increase in the share of managers: possible explanations are an increased complexity in managing the production process or a more suitable application of WFH in firms with more result-oriented jobs (such as those of managers).

The finding that the impact does not systematically differ by major observables such as firm's sector or size does not necessarily imply that it is homogeneous, as firms may differ under a number of observable and unobservable factors. Taking into account the possibility

[27]Coefficients are almost never significant or the estimates are not supported by a robust first stage. The results for the short-run model are reported in Appendix 3.

[28]The investment variable is available as a factor variable of 5 classes. We create one sub-group for the first two classes (0 or less than 5%) and the other subgroup for the other three classes. Table 1.7 only reports labour productivity in terms of revenues but the same result holds also when it is measured in quantities.

of heterogeneous effects is also important because, under their occurrence, the IV would just capture the local effect on the group of firms that used WFH only because that instrument induced them to do so, thus not allowing us to estimate any heterogeneity. Moreover, our LATE does not need to correspond to the average effect.[29] The possible disconnect between the LATE and the ATE can be due to a —very likely— selection on gains, i.e. firms choose WFH only if they know that it will boost their productivity and other firm-level outcomes, a consideration that seems reasonable ex ante. Thus, to study the potential heterogeneity in the effects of WFH we turn to the marginal treatment effect (MTE) framework (Heckman and Vytlacil, 1999, 2007; Cornelissen, Dustmann, Raute, and Schönberg, 2016). Such an approach allows us to relate the unobserved propensity to select into the treatment, i.e. the use of WFH in our setting, which varies across firms, to the heterogeneity in the effects and to recover the ATE.

Let us give some intuition. Our instrument per se does not induce all firms to adopt WFH. Some firms are averse to the treatment —or resist it, in MTE terminology— even when the instrumental variable should induce them to do so, because of observed and unobserved factors that could also affect their potential outcomes, meaning that the treatment effects are heterogeneous. The MTE approach allows us to estimate such aversion (or resistance) to adopting WFH, under additional assumptions that we explain below, and relate it to the effects of WFH. That is, if the MTE decreases with resistance, firms that are more reluctant to adopt will benefit less from increasing WFH intensity. Conversely, if MTE increases with resistance, reluctant firms would benefit the most from a small increase in WFH intensity. The key to determining the selection into treatment is estimating the propensity score, i.e., the probability that a firm adopts WFH given the interaction between the speed of broadband internet connection in its commuting zone and the share of jobs that are potentially workable remotely in its sector of activity. The intuition for the role of the propensity score in MTE is as follows: firms adopt WFH if their interest in it, as measured by the propensity score, exceeds a certain quantile of the distribution of unobserved aversion. In other words, the incentive to be treated, determined by the observed covariates and the instrument, exceeds the unobserved aversion to the treatment (Cornelissen et al., 2016). In Subsection 5.3, we additionally show that such resistance positively correlates also with the inability of firms to predict future use of WFH.

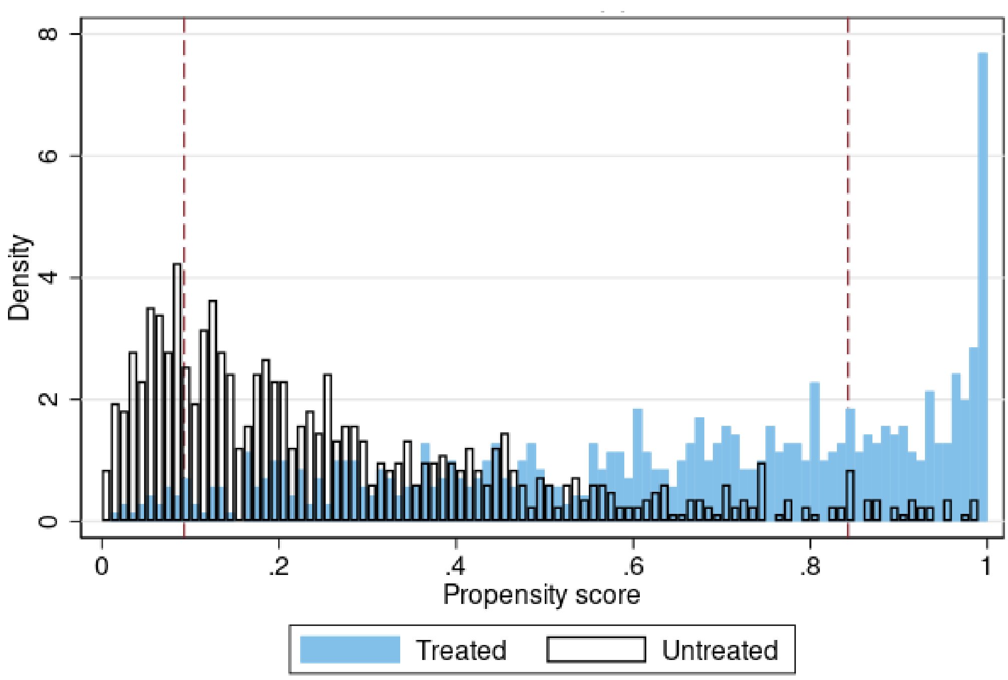
With respect to the assumptions outlined in Section 3.3, we need first that the unobserved components of the potential outcomes and the latent index for WFH adoption —the resistance to treatment— are independent of the instrument, conditional on controls. Second, the unobserved components of the potential outcomes and the latent index of treatment choice must be correlated. Finally, to estimate the propensity score, we need a continuous instrument with

[29]More specifically, as our IV is continuous, we estimate a variance-weighted average of covariate-specific LATEs.

sufficient variation to estimate the propensity score on the full joint support of the covariates. We can only rely on a limited common support due to the small sample size: Figure 4 reports the distribution of the propensity score to adopt WFH.

We estimate the propensity score by running a probit model where the dependent variable is a dummy equal to one if the change in the use of WFH in the 2019-2021 period is above the sample median. In the model, we include the same covariates and the instrumental variable as in the baseline model presented in the previous Sections.

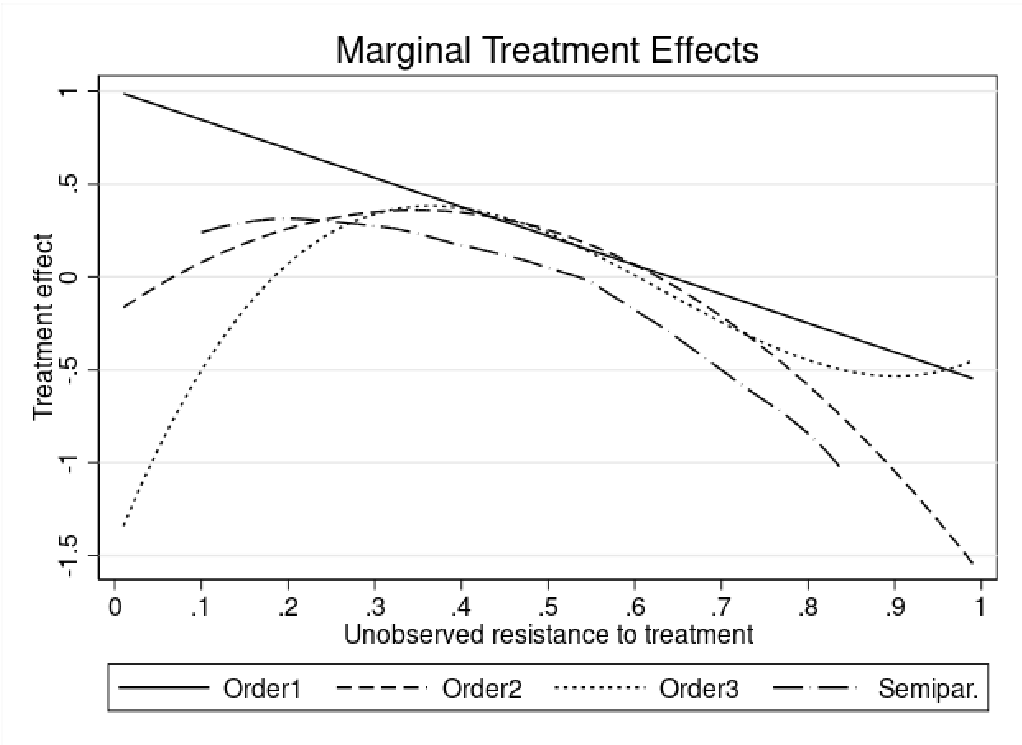
Figure 4: Common support



Notes: The figure shows the supports for treated and untreated firms based on the propensity score for the probability that firm's change in WFH in the 2019-2021 period is above the sample median. The dashed vertical lines delimit the common support area in the semi-parametric estimation. Observations are weighted using INVIND survey weights.

Then, we estimate the MTE in the medium run by assuming that the potential outcomes are a linear function of the covariates and a polynomial function of the propensity score; we consider a polynomial of order from one to three. Following Cornelissen et al. (2016), we also estimate the semi-parametric MTE: although the limited variation we rely on does not allow us to fully trust the semi-parametric estimates, the shape of the curve can be a useful guidance in the choice of the most appropriate modeling framework. We find that in the interval where the common support is thicker (at intermediate levels of resistance to treatment), all specifications suggest a negative slope (Figure 5). This is consistent with a selection on a sensible direction: higher resistance to WFH corresponds to decreasing benefits.

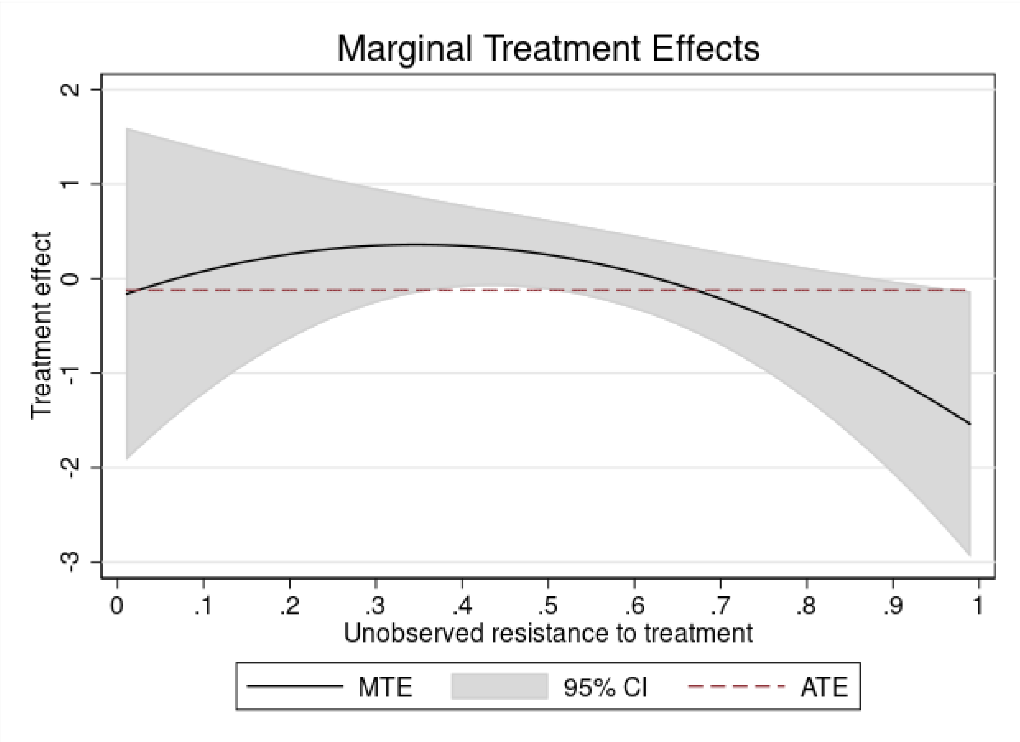
Figure 5: MTE under different polynomial specifications



Notes: The figure shows the MTE obtained under different specifications of the polynomial function of the propensity score and under a semi-paramteric approach. The dependent variable is the change in hourly labour productivity (measured in terms of revenues) between 2019 and 2023. Observations are weighted using INVIND survey weights.

If we look at the whole support (thus including areas where the common support is narrower), the non-parametric pattern seems to be better mimicked by the second order polynomial. Hence, we keep this specification in the main MTE analysis reported in Figure 6. The Figure plots the marginal treatment effects at each quantile of the (latent) resistance index distribution, which we recover from the propensity score as described above. The results indicate that, while the average ATE is overall close to zero (-0.33 percentage points), for an interior interval of the unobserved resistance to treatment the impact of WFH on labour productivity is positive and significant.[30] In other terms, a subset of firms benefitted from WFH in terms of productivity.[31]

Figure 6: Marginal treatment effects on hourly labour productivity in the medium run



Notes: The figure shows the MTE and the 95% confidence interval over the resistance distribution on the change in labour productivity (measured in terms of revenues and hours) between 2019 and 2023. The method used is a polynomial of order 2. Observations are weighted using INVIND survey weights. The dashed line represents the ATE.

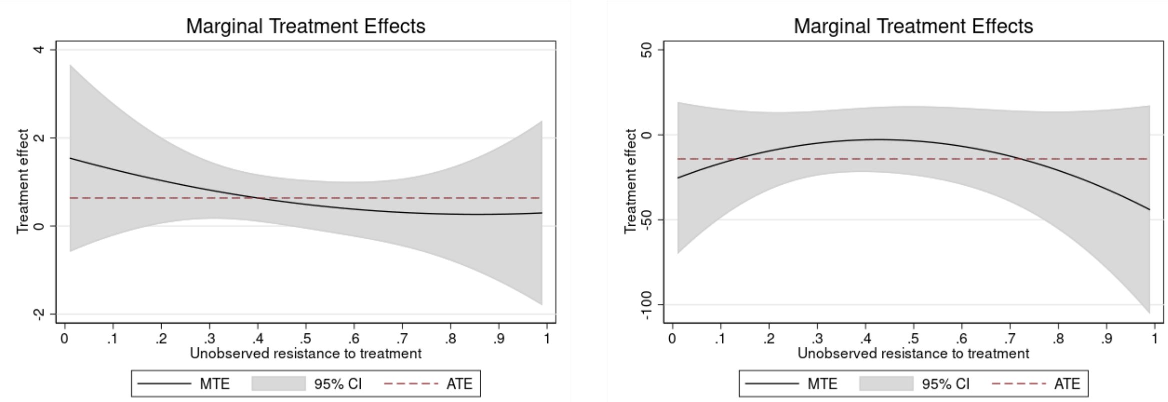
[30]The possible concern of a (unbiased) measurement error in hours worked at home can actually only strengthen the finding of a positive impact as the positive effect emerges despite the potential attenuation caused by measurement error. The presence of a biased misreporting in the measurement of hours does not appear supported by evidence in the main analysis (see Section 4).

[31]A similar pattern as in Figure 6 emerges when we consider labour in terms of headcounts or firm's performance in volumes, but statistical significance is slightly weaker than 5%.

5.2 Heterogeneous persistence across firms

We now test whether firms that benefited in terms of labour productivity showed greater persistence in the use of WFH. This result would corroborate the evidence that the diffusion of WFH during the Covid-19 pandemic might have alleviated the friction to adopt such work arrangement for at least some firms. In Figure 1, we show that despite a general decline, WFH did not fully return to pre-pandemic levels. To test whether firms with greater persistence are also those whose productivity improved thanks to WFH, we rely again on the MTE approach. We estimate persistence in the use of WFH as a function of the unobserved resistance to adopt WFH during the pandemic period (2020-2021). We consider two measures of persistence: one in terms of extensive margin, defined as a dummy equal to one if the use of WFH is higher than the pre-pandemic level in both 2021 and 2023, and one in terms of intensive margin, defined as the change between 2021 and 2023. Figure 7 shows the results. Indeed, the firms that gained the most in terms of labour productivity are also those whose WFH use was more persistent in the post-pandemic period (Figure 7a): the results are significantly different from zero at the 95% level around a resistance level of .2-.4, corresponding to the range for which we found a positive effect on labour productivity (see Figure 6). In terms of intensity of WFH use, the effects are not statistically significant, but the decline is less pronounced —at least qualitatively— for the same group of firms (those in the middle of the resistance distribution; Figure 7b).

Figure 7: The use of WFH, 2019-2023



(a) Extensive margin

(b) Intensive margin

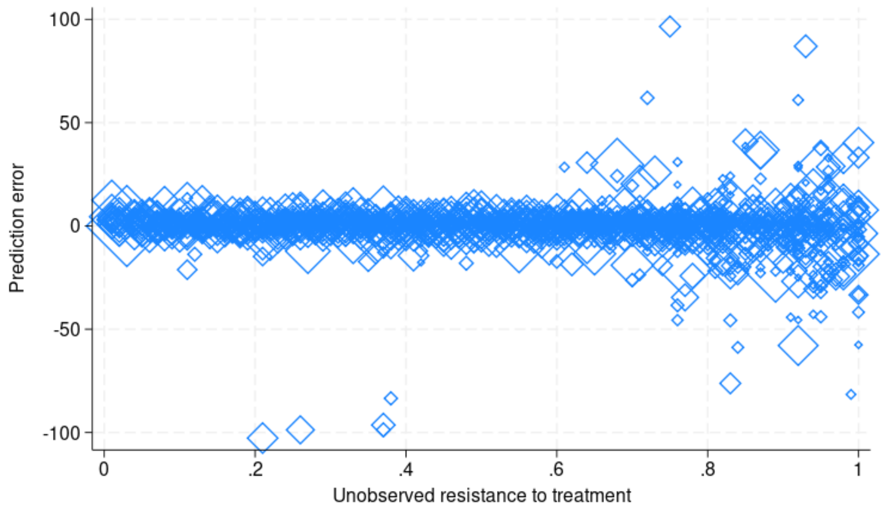
Notes: The figure shows the MTE and the 95% confidence interval over the resistance distribution on the change in the persistence of WFH use (extensive margin; panel a) and its change (intensive margin; panel b) between 2021 and 2023. The method used is a polynomial of order 2. Observations are weighted using INVIND survey weights. The dashed line represents the ATE.

5.3 Ex ante frictions to WFH adoption correlate with knowledge about WFH

Our last piece of evidence aims to show that resistance to adoption correlates with little knowledge about WFH, proxied by the inability to form correct expectations about future use. In the first month of 2021, we asked firms through the INVID survey about their long-run expectations on the share of workers who would work from home.

Figure 8 shows the correlation between the difference in the prediction of future use, as of 2021, and the actual use in 2023 (both as a percentage of the firm workforce) and the estimated MTE resistance to treatment.[32] While such replies could be partly affected by uncertainty during the pandemic, which was not fully over in 2021, it is remarkable how the ex post prediction error is concentrated only on the high end of the ex ante resistance to treatment (recall that the MTE propensity score is measured based on pre-pandemic variables).

Figure 8: Frictions and prediction error in the use of WFH



Notes: The figure shows the correlation between the prediction error in WFH adoption at the firm level between 2021 (prediction) and 2023 (actual use) and the MTE resistance. The size of the bubbles represent the INVIND survey weights.

This result, although descriptive, shows that the firms with the highest resistance to treatment were also those with the largest error in prediction: frictions to adopt were also a matter of knowledge about WFH.

Although the pandemic was an experience about WFH for virtually all firms, the evidence that we present in this paper shows that it alleviated frictions only for firms that were relatively

[32]We present the prediction error residualized with respect to all the covariates included in the MTE analysis. The evidence is robust if we run the unconditional correlation between prediction error and resistance to treatment and if we express the prediction error as a share of the expected use of WFH in the future.

more knowledgeable about these work arrangements (such as those with low to medium ex ante resistance). These firms turned out to be more likely to gain in terms of labour productivity and keep WFH beyond the emergency. Conversely, high-resistance firms had little ex ante knowledge and cut more on WFH adoption once the pandemic was over as adoption was more difficult at the onset of the pandemic and they did not experience gains in labour productivity afterwards.

6 Conclusions

In this paper, we examine the impact of working from home on labour productivity, as well as its persistence following the pandemic. To do so, we used comprehensive administrative and survey datasets on Italian firms covering the period from 2019 to 2023, and we employed an instrumental variable strategy based on pre-determined conditions that facilitated the adoption of WFH when the Covid-19 pandemic hit in 2020.

After spiking during the pandemic, WFH declined overall, but many firms continued to use it. Adoption varied considerably by geography and sector. Pre-existing firm characteristics, such as investment in digital technologies, a higher proportion of female employees and structured management practices, were important determinants.

We find that, on average, WFH neither enhanced nor hindered labour productivity. It had a negligible impact on firm output (whether measured on revenues or quantities), labour input (headcounts or hours worked), and it did not affected the composition of the workforce, profits, variable costs, or investments in 4.0 technologies. Most importantly, we uncover a great deal of heterogeneity between firms. For a subset of firms, we detect productivity gains from the pandemic-induced shift to remote work as revealed by the marginal treatment effect analysis for firms featuring ex ante less resistance to WFH adoption.

We further show that firms that benefited in terms of labour productivity during the pandemic continue to use WFH practices. These results therefore suggest that positive experiences of working from home may have alleviated ex ante concerns about it. In contrast, firms that were highly resistant to WFH pre-pandemic experienced worse productivity effects and were less likely to continue using remote work after the emergency. Interestingly, these firms were also those with less knowledge about WFH arrangements —as captured by less accurate prediction in future use. Taken together, these findings suggest that uncertainty plays a significant role in the implementation of WFH, and that the mass social experiment triggered by the pandemic alleviated these issues for only a subset of firms. This highlights the role of firm heterogeneity in the adoption, persistence, and impact of WFH on labour productivity.

There could be additional gains and losses that are not captured in the time frame we study and with the available data. This paper suggests several areas for future research, such as the impact on longer-term workers' labour market outcomes and welfare (looking even beyond wages) and the need to take into account labour supply considerations —such as investments in human capital and commuting decisions and effects on labour market participation choices (Boeri and Rigo, 2025; Crescenzi, Dottori, and Rigo, 2025). Further research on hiring practices, investments in advanced digital technologies, management practices, and learning-by-doing must account for heterogeneous effects across firms.

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Appendices

1 Additional tables and figures

Table 1.1: Persistence of WFH

	Δ_{19-21} WFH	Δ_{19-21} WFH	Δ_{19-23} WFH	Δ_{19-23} WFH
Δ_{19-20} WFH	0.633***	0.486***		
	(0.072)	(0.075)		
Δ_{19-21} WFH			0.517***	0.416***
			(0.044)	(0.070)
N	1563	1563	1563	1563
R^2	0.537	0.714	0.585	0.722

Notes: All regressions are weighted using INVIND survey weights. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses.* $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$

Table 1.2: Firms' characteristics by WFH Status, 2021

	WFH in 2021		
	Yes	No	Total
N	826 (52.8%)	737 (47.2%)	1,563 (100.0%)
$\frac{Revenues}{Hours}_{2017-2019}$	0.20 (0.44)	0.40 (1.76)	0.29 (1.25)
$\text{Revenues}_{2017-2019}$	37122.34 (1.2e+05)	3.6e+05 (1.9e+06)	1.9e+05 (1.3e+06)
$\text{Hours}_{2017-2019}$	2.2e+05 (6.4e+05)	1.3e+06 (7.9e+06)	7.4e+05 (5.5e+06)
$\frac{Volume}{Hours}_{2017-2019}$	0.26 (0.62)	0.78 (5.42)	0.51 (3.76)
$\text{Volume}_{2017-2019}$	49263.80 (1.9e+05)	6.7e+05 (4.4e+06)	3.4e+05 (3.0e+06)
$\frac{Volume}{Empl}_{2017-2019}$	451.41 (1123.66)	1257.66 (8782.16)	831.58 (6096.73)
$\frac{Revenue}{Empl}_{2017-2019}$	337.66 (793.05)	648.23 (2805.69)	484.10 (2016.29)
$\text{Empl}_{2017-2019}$	148.54 (554.12)	863.97 (5310.21)	485.89 (3684.65)
Proxy WFH-able	0.23 (0.14)	0.32 (0.21)	0.28 (0.18)
WFH2019	0.04 (0.18)	0.21 (0.41)	0.12 (0.32)
Cloud2017-2019	0.23 (0.42)	0.45 (0.50)	0.33 (0.47)
Sh. fixed $\text{term}_{2017-2019}$	0.08 (0.11)	0.05 (0.08)	0.06 (0.10)
Sh. $\text{managers}_{2017-2019}$	0.01 (0.02)	0.02 (0.03)	0.01 (0.02)
Sh. white $\text{collars}_{2017-2019}$	0.28 (0.20)	0.50 (0.30)	0.39 (0.27)
Sh. $\text{female}_{2017-2019}$	0.25 (0.22)	0.28 (0.20)	0.26 (0.21)
Sh. $\text{young}_{2017-2019}$	0.18 (0.12)	0.18 (0.12)	0.18 (0.12)
Sh. hourly $\text{wage}_{2017-2019}$	376.35 (321.84)	260.47 (333.46)	321.71 (332.34)
$\text{Wages}_{2017-2019}$	2827.09 (3281.89)	5423.79 (8809.95)	4051.51 (6628.85)
$\text{Costs}_{2017-2019}$	6222.61 (13641.78)	82321.57 (4.2e+05)	42251.33 (2.9e+05)

Notes: Standard deviations in parentheses.

Table 1.3: Test for correlation between instrument and covariates

	Avg.bb speed*Proxy WFH-able
Avg. bb. speed	0.332**
	(0.018)
Proxy WFH-able	156.588**
	(15.237)
Cloud	-1.598
	(2.870)
Sh. fixed term	-27.488**
	(9.861)
Sh. female	-2.900
	(7.506)
Avg. wage	0.000
	(0.000)
Sh. export	-0.684
	(5.364)
Firm age	0.053
	(0.049)
p-value (size F.E. = 0)	0.302
p-value (group F.E. = 0)	0.124
p-value (sector-area F.E. = 0)	0.000
N	1563
R^2	0.878

Notes: All regressions are weighted using INVIND survey weights. The dependent variable (IV) is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses.* $p < 0.05$, ** $p < 0.01$,*** $p < 0.001$

Table 1.4: WFH, investments in 4.0 technologies, and costs

	(1) Δ_{19-23} inv. max	(2) Δ_{19-23} inv. dummy	(3) Δ_{19-23} var. costs
Panel a. OLS			
Δ_{19-21} WFH	0.005	0.001	-0.000
	(0.005)	(0.001)	(0.001)
Panel b. 2SLS			
Δ_{19-21} WFH	-0.016	-0.007	-0.004
	(0.024)	(0.007)	(0.006)
AR bounds	[-0.088, 0.025]	[-0.029, 0.005]	[-0.018, 0.007]
OP F-stat	15.7	15.7	12.4
N	1549	1549	1482

Notes: All regressions are weighted using INVIND survey weights. The dependent variable is: in col. (1), the highest amount (in classes) invested in 4.0 technologies after 2019 and up to 2023; in col. (2), a dummy indicating whther the firm has done an investment in 4.0 technology ater 2019 and up to 2023; in col. (3), the log difference in variable costs between 2019 and 2023. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 1.5: Medium run effects of WFH by firm size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{19-23}\log(\frac{revenues}{hours})$		$\Delta_{19-23}\log(wage_{all})$		$\Delta_{19-23}\log(wage_{wh.col.})$		Δ_{19-22}var. costs	
	Smaller	Larger	Smaller	Larger	Smaller	Larger	Smaller	Larger
Δ_{19-21} WFH	-0.003	-0.003	-0.001	0.003	-0.004	-0.000	-0.002	-0.002
	(0.007)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.008)	(0.006)
OP F-stat	6.2	12.9	6.2	12.9	6.2	12.9	5.5	14.2
N	504	1059	504	1059	501	1056	473	1024
	Δ_{19-22} Sh.managers		Δ_{19-22} Sh.white-collars		Δ_{19-22} Sh.female		Δ_{19-22} Sh.young	
	Smaller	Larger	Smaller	Larger	Smaller	Larger	Smaller	Larger
Δ_{19-21} WFH	-0.000	0.000	0.001	0.001	-0.000	-0.001*	-0.002	-0.001
	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
OP F-stat	6.2	12.9	6.2	12.9	6.2	12.9	6.2	12.9
N	504	1059	504	1059	504	1059	504	1059

Notes: All regressions are weighted using INVIND survey weights. Sub-samples are defined by grouping the four size-bins in two classes: the "smaller" firms, made by the first two size categories, include firms with less than 50 employees; the "larger" firms, made by the other two categories, include firms with 50 employees or more. For the employment shares, the last year of analysis is 2022 due to a lag in the availability of data. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 1.6: Medium-run effects of WFH by macro sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{19-23}\log(\frac{revenues}{hours})$		$\Delta_{19-23}\log(wage_{all})$		$\Delta_{19-23}\log(wage_{wh.col.})$		Δ_{19-22}var. costs	
	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.
Δ_{19-21} WFH	0.003	0.001	0.009*	0.001	0.004	-0.001	-0.015	-0.000
	(0.008)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.016)	(0.006)
OP F-stat	3.7	11.4	3.7	11.4	3.7	11.4	3.3	11.8
N	1043	443	1043	443	1041	439	999	424
	Δ_{19-22} Sh.managers		Δ_{19-22} Sh.white-collars		Δ_{19-22} Sh.female		Δ_{19-22} Sh.young	
	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.
Δ_{19-21} WFH	0.001	-0.000	0.001	0.001	0.001	-0.001	-0.001	-0.002
	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
OP F-stat	3.7	11.4	3.7	11.4	3.7	11.4	3.7	11.4
N	1043	443	1043	443	1043	443	1043	443

Notes: Medium-run effects of WFH by sector: manufacturing vs. services. All regressions are weighted using INVIND survey weights. For employment shares, the last year of analysis is 2022 due to a lag in the availability of data. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 1.7: Firms that had invested (or not) in 4.0 technologies. Medium run effects of WFH.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{19-23}\log(\frac{revenues}{hours})$		$\Delta_{19-23}\log(wage_{all})$		$\Delta_{19-23}\log(wage_{w.c.})$		Δ_{19-22}var. costs	
	No	Yes	No	Yes	No	Yes	No	Yes
$\Delta_{19-21}WFH$	0.002	0.008^{+}	0.004	0.001	0.003	-0.002	0.010	-0.009
	(0.008)	(0.005)	(0.007)	(0.002)	(0.007)	(0.002)	(0.009)	(0.006)
OP F-stat	5.8	10.0	5.8	10.0	5.8	10.1	6.7	10.1
N	917	646	917	646	912	645	873	624

	Δ_{19-22} Sh.managers		Δ_{19-22} Sh.white-collars		Δ_{19-22} Sh.female		Δ_{19-22} Sh.young	
	No	Yes	No	Yes	No	Yes	No	Yes
$\Delta_{19-21}WFH$	-0.001	0.001^{+}	0.002	0.001	-0.002	-0.000	-0.001	0.000
	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
OP F-stat	5.8	10.0	5.8	10.0	5.8	10.0	5.8	10.0
N	917	646	917	646	917	646	917	646

Notes: All regressions are weighted using INVIND survey weights. Firms are in the group ‘es” if before the pandemic they invested at least 5% of their yearly revenues in 4.0 technologies. For employment composition, . $wage_{all}$ and $wage_{W.C.}$ refer to the average wage of, respectively, all employees and non-manager white-collar employees only; $var.costs$ refers to variable costs; the bottom panel refers to workforce composition (for which the last year is 2022 due to data availability) in terms of employment share of: managers, non-manager white-collar employees; female employees; 15-34 years old employees. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm’s age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

2 Alternative samples

We conduct the main analysis on the same sample of firms across years in order to have a better comparability across periods and specifications, and exploit a stronger identification power ((as measured by the F-stat). In this Appendix, we show that the results are basically confirmed if the short-run and the medium-run analyses are carried out on two distinct samples, thus increasing the number of observations in each model (above two thousands).

In the short run (2019-2021), the increase in WFH appeared to not have harmed firms' productivity (Table 2.1, panel A), neither firm sales nor labour input (panel B), neither employment mix nor wages (panel C and D, respectively).

As shown in Table 2.2, also in the medium run (2019-2023) no significant harmful effect on productivity is detected, with neutrality regarding both firm sales and labour input. With respect to employment mix and wages —for which the period is 2019-2022 due to data availability— we find no significant effect as well. Also the evidence of no significant effect on investment in digital technologies is confirmed.

Table 2.1: Alternative sample: short run (2019-2021), 2SLS estimates

	(1)	(2)	(3)	(4)
Panel A. Labour productivity				
	$\Delta_{19-21}\log(\frac{revenues}{hours})$	$\Delta_{19-21}\log(\frac{revenues}{employm.})$	$\Delta_{19-21}\log(\frac{volumes}{hours})$	$\Delta_{19-21}\log(\frac{volumes}{employm.})$
Δ_{19-21} WFH	0.005	0.005	0.005	0.005
	(0.005)	(0.007)	(0.005)	(0.007)
AR bounds	[-0.006, 0.021]	[-0.008, 0.025]	[-0.006, 0.020]	[-0.008, 0.025]
OP F-stat	10.5	10.5	10.5	10.5
N	2343	2343	2343	2343
Panel B. Firm performance and labour				
	$\Delta_{19-21}\log(revenues)$	$\Delta_{19-21}\log(volumes)$	$\Delta_{19-21}\log(hours)$	$\Delta_{19-21}\log(employm.)$
Δ_{19-21} WFH	0.001	0.001	-0.004	-0.005
	(0.007)	(0.007)	(0.005)	(0.003)
AR bounds	[-0.016, 0.017]	[-0.016, 0.017]	[-0.019, 0.005]	[-0.016,-0.000]
OP F-stat	10.5	10.5	10.5	10.5
N	2343	2343	2343	2343
Panel C. Employment mix				
	Δ_{19-21} Sh. managers	Δ_{19-21} Sh.white-collars	Δ_{19-21} Sh.female	Δ_{19-21} Sh.young
Δ_{19-21} WFH	0.000	0.000	-0.001	-0.002
	(0.000)	(0.002)	(0.001)	(0.001)
AR bounds	[-0.000, 0.000]	[-0.004, 0.005]	[-0.003, 0.001]	[-0.006, 0.000]
OP F-stat	10.5	10.5	10.5	10.5
N	2343	2343	2336	2336
Panel D. Workers' compensation				
	$\Delta_{19-21}\log(hourly\,wage)$ all employees	$\Delta_{19-21}\log(monthly\,w)$ all employees	$\Delta_{19-21}\log(monthly\,w)$ white-collars	$\Delta_{19-21}\log(monthly\,w)$ blue-collars
Δ_{19-21} WFH	0.004	-0.001	-0.000	0.011
	(0.004)	(0.004)	(0.003)	(0.010)
AR bounds	[-.003, .017]	[-.009, .009]	[-.007, .008]	[-.005, ...]
OP F-stat	10.5	10.5	10.5	4.3
N	2336	2336	2327	2165

Notes: All regressions are weighted using INVIND survey weights. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 2.2: Alternative sample: Medium run, 2SLS estimates

	(1)	(2)	(3)	(4)
Panel A. Labour productivity (2019-2023)				
	$\Delta_{19-23}\log(\frac{revenues}{hours})$	$\Delta_{19-23}\log(\frac{revenues}{employm.})$	$\Delta_{19-23}\log(\frac{volumes}{hours})$	$\Delta_{19-23}\log(\frac{volumes}{employm.})$
Δ_{19-21} WFH	0.000	0.003	-0.000	0.002
	(0.005)	(0.004)	(0.005)	(0.004)
AR bounds	[-0.011, 0.012]	[-0.005, 0.014]	[-0.012, 0.011]	[-0.006, 0.013]
OP F-stat	9.8	9.8	9.8	9.8
N	2038	2038	2038	2038
Panel B. Firm performance and labour (2019-2023)				
	$\Delta_{19-23}\log(revenues)$	$\Delta_{19-23}\log(volumes)$	$\Delta_{19-231}\log(hours)$	$\Delta_{19-23}\log(employm.)$
Δ_{19-21} WFH	-0.003	-0.003	-0.003	-0.005
	(0.005)	(0.005)	(0.004)	(0.004)
AR bounds	[-0.018, 0.006]	[-0.019, 0.006]	[-0.017, 0.004]	[-0.021, 0.000]
OP F-stat	9.8	9.8	9.8	9.8
N	2038	2038	2038	2038
Panel C. Employment mix (2019-2022)				
	Δ_{19-22} Sh.managers	Δ_{19-22} Sh.white-collars	Δ_{19-22} Sh.female	Δ_{19-22} Sh.young
Δ_{19-21} WFH	-0.000	-0.001	-0.001	-0.001
	(0.000)	(0.002)	(0.001)	(0.001)
AR bounds	[-0.001, 0.001]	[-0.001, 0.003]	[-0.002, 0.001]	[-0.004, 0.001]
OP F-stat	9.8	9.8	9.8	9.8
N	2038	2038	2034	2034
Panel D. Workers' compensation (2019-2022)				
	$\Delta_{19-22}\log(hourly\,wage)$ all employees	$\Delta_{19-21}\log(monthly\,w)$ all employees	$\Delta_{19-22}\log(monthly\,w)$ white-collars	$\Delta_{19-22}\log(monthly\,w)$ blue-collars
Δ_{19-21} WFH	0.002	0.003	0.002	0.022
	(0.005)	(0.004)	(0.003)	(0.022)
AR bounds	[-0.008, 0.012]	[-0.004, 0.010]	[-0.006, 0.006]	[0.002, 0.047]
OP F-stat	9.8	9.8	9.8	1.4
N	2034	2034	2024	1887

Notes: All regressions are weighted using INVIND survey weights. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

3 Additional tables for the short-run period

Table 3.1: WFH and labour productivity: Short run

	(1) $\Delta_{19-21}\log(\frac{revenues}{hours})$	(2) $\Delta_{19-21}\log(\frac{revenues}{employm.})$	(3) $\Delta_{19-21}\log(\frac{volumes}{hours})$	(4) $\Delta_{19-21}\log(\frac{volumes}{employm.})$
Panel a. OLS				
Δ_{19-21} WFH	-0.001	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Panel b. 2SLS				
Δ_{19-21} WFH	0.003	0.004	0.003	0.004
	(0.005)	(0.006)	(0.005)	(0.006)
AR bounds	[-0.056, 0.013]	[-0.054, 0.010]	[-0.059, 0.012]	[-0.057, 0.009]
OP F-stat	15.7	15.7	15.7	15.7
N	1563	1563	1563	1563
Pre-2020 avg. outcome	0.293	484.1	0.507	831.6

Notes: All regressions are weighted using INVIND survey weights. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 3.2: WFH, firm performance and labour: Short run

	(1) $\Delta_{19-21}\log(revenues)$	(2) $\Delta_{19-21}\log(volumes)$	(3) $\Delta_{19-21}\log(hours)$	(4) $\Delta_{19-21}\log(employm.)$
Panel a. OLS				
Δ_{19-21} WFH	0.000	0.000	0.001+	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Panel b. 2SLS				
Δ_{19-21} WFH	0.002	0.002	-0.001	-0.002
	(0.006)	(0.006)	(0.004)	(0.002)
AR bounds	[-0.001, 0.012]	[-0.010, 0.018]	[-0.009, 0.007]	[-0.007, 0.001]
OP F-stat	15.7	15.7	15.7	15.7
N	1563	1563	1563	1563
Pre-2020 avg. outcome	191.4	342.3	740.4	486

Notes: All regressions are weighted using INVIND survey weights. The pre-2020 avg. otucomes in columns (1), (2) are in millions of euro, in column (3) in thousands of hours. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors in parentheses are clustered at the province-sector level. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table 3.3: WFH and employment mix: Short run

	(1) Δ_{19-21} Sh.managers	(2) Δ_{19-21} Sh.white-collars	(3) Δ_{19-21} Sh.female	(4) Δ_{19-21} Sh.young
Panel a. OLS				
Δ_{19-21} WFH	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel b. 2SLS				
Δ_{19-21} WFH	-0.000	0.001	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)
AR bounds	[-0.000, 0.000]	[-0.000, 0.004]	[-0.002, 0.001]	[-0.004, 0.000]
OP F-stat	15.7	15.7	15.7	15.7
N	1563	1563	1563	1563
Pre-2020 avg. outcome	1.3%	38.8%	26.0%	18.0%

Notes: All regressions are weighted using INVIND survey weights. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 3.4: WFH and workers' compensation: Short run

	(1) $\Delta_{19-21}\log(hourly\,wage)$ all employees	(2) $\Delta_{19-21}\log(monthly\,w)$ all employees	(3) $\Delta_{19-21}\log(monthly\,w)$ white-collars	(4) $\Delta_{19-21}\log(monthly\,w)$ blue-collars
Panel a. OLS				
Δ_{19-21} WFH	-0.001+	-0.000	-0.000	-0.001
	(0.001)	(0.000)	(0.000)	(0.001)
Panel b. 2SLS				
Δ_{19-21} WFH	-0.000	-0.001	-0.003	0.011+
	(0.003)	(0.003)	(0.002)	(0.006)
AR bounds	[-0.007, 0.007]	[-0.007, 0.006]	[-0.008, 0.003]	[0.002, 0.040]
OP F-stat	15.7	15.7	15.7	7.4
N	1563	1563	1558	1445
Pre-2020 avg. outcome	321.7	4052	4717	2878

Notes: All regressions are weighted using INVIND survey weights. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 3.5: Firms that had invested (or not) in 4.0 technologies. Short run effects of WFH

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ_{19-21} log($\frac{revenues}{hours}$)		Δ_{19-21} log($wage_{all}$)		Δ_{19-21} log($wage_{wh.col.}$)		Δ_{19-21} var. costs	
	No	Yes	No	Yes	No	Yes	No	Yes
Δ_{19-21} WFH	0.015	0.003	0.007	-0.006^{+}	0.003	-0.007^{+}	0.021	-0.016*
	(0.009)	(0.004)	(0.006)	(0.003)	(0.005)	(0.004)	(0.014)	(0.008)
OP. F-stat	5.766	10.039	5.766	10.039	5.790	10.039	5.091	10.325
N	917	646	917	646	912	646	888	626
	Δ_{19-21}Sh.managers		Δ_{19-21} Sh.white-collars		Δ_{19-21}Sh.female		Δ_{19-21}Sh.young	
	No	Yes	No	Yes	No	Yes	No	Yes
Δ_{19-21} WFH	0.000	-0.000	0.003	0.001	-0.000	-0.001*	-0.002	-0.000
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
OP. F-stat	5.766	10.039	5.766	10.039	5.766	10.039	5.766	10.039
N	917	646	917	646	917	646	917	646

Notes: All regressions are weighted using INVIND survey weights. Firms are in the group "Yes" if before the pandemic they invested at least 5% of their yearly revenues in 4.0 technologies. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 3.6: Short run effects by firm size

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δ_{19-21} log($\frac{revenues}{hours}$)		Δ_{19-21} log($wage_{all}$)		Δ_{19-21} log($wage_{wh.col.}$)		Δ_{19-21}var. costs	
	Smaller	Larger	Smaller	Larger	Smaller	Larger	Smaller	Larger
Δ_{19-21} WFH	0.010	-0.004	-0.001	-0.001	-0.003	-0.003	0.001	-0.004
	(0.009)	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.008)	(0.010)
OP. F-stat	6.189	12.867	6.189	12.867	6.208	12.866	4.576	12.317
N	504	1059	504	1059	502	1056	479	1035
	Δ_{19-21}Sh.managers		Δ_{19-21} Sh.white-collars		Δ_{19-21}Sh.female		Δ_{19-21}Sh.young	
	Smaller	Larger	Smaller	Larger	Smaller	Larger	Smaller	Larger
Δ_{19-21} WFH	-0.000	0.000	0.001	0.001	-0.001	-0.000	-0.002	-0.000
	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
OP. F-stat	6.189	12.867	6.189	12.867	6.189	12.867	6.189	12.867
N	504	1059	504	1059	504	1059	504	1059

Notes: All regressions are weighted using INVIND survey weights. Sub-samples are defined by grouping the four size-bins in two classes: the "smaller" firms, made by the first two size categories, include firms with less than 50 employees; the "larger" firms, made by the other two categories, include firms with 50 employees or more. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 3.7: Short run effects by macro sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta_{19-21}\log(\frac{revenues}{hours})$		$\Delta_{19-21}\log(wage_{all})$		$\Delta_{19-21}\log(wage_{wh.col.})$		Δ_{19-21}var. costs	
	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.
Δ_{19-21} WFH	0.003	0.001	0.009*	0.001	0.004	-0.001	-0.015	-0.000
	(0.008)	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.016)	(0.006)
OP. F-stat	3.688	11.395	3.688	11.395	3.689	11.494	3.281	11.799
N	1043	443	1043	443	1041	439	999	424

	Δ_{19-21}Sh.managers		Δ_{19-21} Sh.white-collars		Δ_{19-21}Sh.female		Δ_{19-21}Sh.young	
	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.	Manuf.	Serv.
Δ_{19-21} WFH	0.001	-0.000	0.001	0.001	0.001	-0.001	-0.001	-0.002
	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
OP. F-stat	3.688	11.395	3.688	11.395	3.688	11.395	3.688	11.395
N	1043	443	1043	443	1043	443	1043	443

Notes: All regressions are weighted using INVIND survey weights. The IV is the interaction between the average broadband (Av.bb) speed, measured as the average broadband speed at the municipality level, and the share of WFH-able workers (Proxy WFH-able), measured at the 3-digit sectoral level. The set of covariates, whose coefficients are not shown in the Table, includes R&D and investments in cloud technology, the share of fixed-term workers of the firm, the share of female workers, the average wage, the share of export, the firm's age, whether the firm belongs to a national or international group or is not part of a conglomerate, the components of the instrument taken separately, fixed effects by size class, and fixed effects by macroarea, sector and macroarea-by-sector. Standard errors clustered at province-sector level in parentheses. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.