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WORK FROM HOME, LABOUR MARKET PARTICIPATION AND EMPLOYMENT

by Riccardo Crescenzi*, Davide Dottori** and Davide Rigo***

Abstract

We examine how the pandemic-driven rise in work from home (WFH) has affected labour market participation and employment in Italy. Leveraging a unique administrative dataset covering the population of remote workers, we find that WFH has had a positive effect on both activity and employment rates at the local labour market (LLM) level. To address endogeneity concerns, we instrument the observed increase in WFH with its potential, derived from LLM sectoral compositions. Controlling for several demographic and economic factors that could affect the distribution of WFH potential, we find no evidence of pre-trends. We also explore the mechanisms driving our results. The impact is stronger in response to the increase in WFH among women of child-rearing age and in areas with limited childcare services. We also find that the effect is more pronounced in the South and in less densely populated areas. These findings suggest that WFH can play a role in terms of labour market inclusion.

JEL Classification: J21, J22, J16, M54, R11, 033.

Keywords: work from home, labour force participation, local labour markets.

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1 Introduction[*]

The Covid-19 pandemic triggered a large-scale social experiment in the organization of work, leading to a remarkable increase in remote work (Barrero *et al.*, 2023; Lee, 2023). Although work-from-home (WFH) levels declined from their peak during the crisis, they have remained persistently higher than pre-pandemic levels (Aksoy *et al.*, 2023b; Bick *et al.*, 2023), often in the form of hybrid arrangements that combine remote and on-site work (Bloom *et al.*, 2023; Choudhury *et al.*, 2024). This shift has been further facilitated by the digitalisation of advanced economies, which has expanded both the feasibility and scope of WFH by reducing the need for physical proximity in many tasks (Barrero *et al.*, 2021; Gathmann *et al.*, 2024; Bai *et al.*, 2021). There is therefore a growing interest in examining the impact of WFH beyond the pandemic period. While recent studies have explored its effects on commuting behaviour (Nagler *et al.*, 2024; Davis *et al.*, 2024; Boeri and Rigo, 2025), wage setting (Cullen *et al.*, 2025), firms' labour demand (Hansen *et al.*, 2023; Bratti *et al.*, 2024), and labour productivity (Boeri *et al.*, 2024; Basso *et al.*, 2025), the available evidence on its medium-term impact on labour market participation is still scant.

In this paper, we investigate the causal impact of WFH on labour force participation and employment using Italian data up to 2023. From a theoretical perspective, WFH may enhance labour market participation by reducing commuting time and costs while offering greater flexibility (Arntz *et al.*, 2022; Black *et al.*, 2014). The hours saved from commuting can be reallocated to work or other responsibilities, enabling individuals to better balance job and home life. This increased flexibility can facilitate labour market entry and retention, particularly for those facing constraints, thereby contributing to higher participation and employment rates. Moreover, WFH can ease job-search frictions by expanding the scope and quality of matching, through an improved alignment between employee's and employer's requirements. However, these benefits may not fully materialize if WFH primarily serves as a complementary arrangement for already employed individuals rather than expanding employment along the extensive margin of labour force participation.

Against this background, Italy provides a relevant case study for three main reasons. First, compared to the other E.U. countries, it has structurally low labour market partici-

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pation, which translates into a lower employment rate. Activity rates are particularly low in the South and among the female population (Accetturo *et al.*, 2022b; Carta, 2019).[1] Improving labour market participation is particularly critical for Italy's long-term economic prospects, given its ageing population and low fertility rates (De Philippis, 2017; Bovini *et al.*, 2023). Second, WFH adoption in Italy was significantly lower than in other E.U. countries before the pandemic, and the country was the first advanced Western economy to experience the full impact of Covid-19 in February-March 2020. As a result, the surge in WFH was both remarkable and unexpected (Crescenzi *et al.*, 2024).[2] Third, to the best of our knowledge, Italy is the only advanced economy that – due to reporting requirements for firms related to public insurance on job accidents – has systematically collected real-time data on the population of employees working from home. This provides us with a unique dataset covering the universe of employees in WFH from 2019 to 2022.

Leveraging these data, we first document the marked heterogeneity in the adoption of WFH across the Italian territory, with higher prevalence in Northern regions and urban areas. Moreover, WFH is more widespread among women than men in all four main macroregions. Crucially, thanks to the granularity of our WFH data, we are able to construct a measure of the increase in WFH at the local labour market level (LLM), disaggregated by gender and age group.

In our empirical model, we assess the impact of the increase in WFH on changes in activity and employment rates at the LLM level. To address endogeneity concerns, following Alipour *et al.* (2021), we use a measure of work-from-home potential (WFHP) as an instrument. Our measure is constructed using a WFHP index at a narrowly defined sectoral level as developed by Basso *et al.* (2022), which is based on the suitability to remote work of occupations in each industry. We then derive a measure of WFHP at the LLM level by weighting this index according to the industries' employment shares in each LLM before the pandemic shock.

Our instrumental variable exploits the exogenous nature of the COVID-19 shock and the inherent technical characteristics of tasks and occupations within each industry, ensuring that it remains stable in the short term and is not influenced by firm-specific factors. Since the WFHP distribution is non-randomly distributed across the Italian territory, we pinpoint and discuss several possible confounding factors that could threaten our identifi-

[1] According to Eurostat data from the Labour Force Survey, the activity rate in the 15-64 age class in Italy was 66.7% in 2023, the lowest among the 27 E.U. countries, whose averages scored at 75.0%. The employment rate in the same age bucket is equal to 61.5% in Italy and 70.4% in the E.U. average. In the "South and Islands" macroregion (henceforth denoted more simply as "South") the activity rate was 56.3%, versus 72.8% in the North. In the country average, the female activity rate was at 57.7%, 18 pp less than the male rate, representing the second highest gender gap in the E.U.. Among women in the South the participation rate is as low as 43.3%, with a gender gap of 26 pp.

[2] According to Eurostat data based on the Labour force Survey, in 2019 more than 95% of people employed in Italy never worked from home, about 10 pp more than the E.U. average.

cation. To address these concerns, we control for predetermined socio-economic variables associated to these confounders and provide evidence supporting the conditional validity of the instrument upon their inclusion. Furthermore, following Borusyak *et al.* (2025), we leverage the large number of industries composing our instrument to demonstrate that identification remains valid at the industry level in aggregate.[3] As part of our robustness checks, we explore alternative instrumental variables, such as an index of WFHP based on Dingel and Neiman (2020) and the broadband speed in the area following Basso *et al.* (2025).

By taking LLMs as units of analysis, we are able to include spillover effects that an analysis at the individual level might overlook. The increased diffusion of WFH has in fact the potential to enhance labour market participation not only by creating more remote jobs but also by raising awareness of WFH opportunities, encouraging a broader group of workers to participate. On the other hand, a more aggregate analysis would reduce the size of the estimation sample and provide a less precise measure of both WFH potential and the workers' exposure to actual WFH in the area. Moreover, analysing WFH at the individual level may suffer from selection bias, as those who choose remote work often have different characteristics - such as higher education - compared to those who do not, whereas an LLM-level approach mitigates this issue by capturing variation across labour markets rather than self-selected individuals.

Our results indicate a positive and significant effect of WFH on both the activity and the employment rate. A one-standard-deviation increase in the number of WFH workers, scaled by the total number of LLM employees, corresponds to a 0.9 percentage point increase in the participation rate and a 0.7 percentage point increase in the employment rate. The richness of the administrative data enables us to examine the heterogeneity of these effects across demographic characteristics of WFH workers. We find that the impact is more pronounced in response to the increase in WFH among individuals aged 25-49, a cohort often engaged in child-care responsibilities. Furthermore, the effect is stronger for the increased use of WFH by women rather than men, particularly within this age group. Given that child-care responsibilities in Italy are predominantly borne by women, these findings suggest to explore heterogeneity with respect to child-care provision.

By exploiting the regional dimension of our analysis, we find that the impact of WFH on labour market participation is concentrated in areas where child-care services are less available. Additionally, WFH appears to play a more significant role in fostering labour market participation (and employment) in less economically advanced regions, such as

[3]In the terminology of Borusyak *et al.* (2025), this corresponds to the *shift* level, i.e. the exposures to a shock that vary along a different dimension than the unit of analysis, onto which they are mapped by the *shares*. While the analytical framework developed by Borusyak *et al.* (2025) remains applicable, we refrain from using the term *shift* as our setting does not involve a time variation as in the canonical Bartik-style measure.

the South and less densely populated LLMs. While WFH is less widespread in these areas, it may still have served as an opportunity that facilitated labour market entry for individuals who might otherwise have remained inactive. In contrast, in the Centre-North and in urban LLMs, where its level is higher, WFH appears to play a less decisive role in influencing individuals' decisions to enter the labour market.

Overall, our findings suggest that WFH can encourage individuals to participate in the labour market and that this effect is more pronounced in disadvantaged areas and following an increase in WFH by groups with traditionally lower activity rates, such as women of child-rearing age. In this regard, our results point to an inclusivity-enhancing role of WFH in the labour market, aligning with Bloom *et al.* (2024), who highlight its positive labour-market effects for individuals with disabilities. These channels could partly counterbalance the threats of increased inequality highlighted by Bonacini *et al.* (2021) based on the higher potential of teleworkability in occupations more frequently performed by men and better paid employees.

Contribution to the literature. This paper contributes to the rapidly expanding literature on the effects of WFH. In particular, it relates to studies examining the impact of WFH on labour outcomes (Biasi *et al.*, 2022; Brinca *et al.*, 2021; Berniell *et al.*, 2023). While most of these studies focus on the pandemic period and highlight the mitigating role of WFH in counteracting the negative effects of the crisis – though not always uniformly – we extend the analysis by examining the impact of WFH on labour market participation and employment over an interval that goes beyond the pandemic, within a relatively stabilized "new normal" context. However, this "new normal" differs from the pre-pandemic earlier periods analysed in other studies (Baruch, 2000; Bloom *et al.*, 2015; Arntz *et al.*, 2022), given the advancements in digital technologies and the widespread familiarity with WFH practices, which were significantly accelerated by their extensive adoption during the pandemic.

Second, as pointed out by Arntz *et al.* (2022), the empirical evidence on the impact of WFH on labour supply is still scant, in particular with respect to the extensive margin. Along the intensive margin, Pabilonia and Vernon (2025) show that in the US remote employees worked more hours than in-presence workers before the pandemic, but by 2021 their hours were similar. Pabilonia and Vernon (2024) find that hybrid WFH – but not full WFH – has a positive effect on hours worked. Dettling (2017) suggests that remote working can be a relevant channel behind her result of a positive effect of internet connection on female labour supply. Other studies provide descriptive evidence based on survey data that rely on employees' self-assessments of remote-work effects (Aksoy *et al.*, 2023a; Bick *et al.*, 2023; Nagler *et al.*, 2024). We contribute by adding evidence based on administrative data on actual WFH adoption, encompassing the entire workforce, and by pursuing a causal analysis. In this respect, we can arguably offer a contribution in terms of external validity with respect to causal evidence on the impact of WFH based on field experiments conducted in specific context (Gibbs *et al.*, 2023; Angelici and Profeta, 2020).

Third, this paper also speaks to the growing literature that analyses WFH in a gender perspective or considering parental duties. Several studies (Del Boca *et al.*, 2020; Inchauste and Siravegna, 2024; Berniell *et al.*, 2023) focus on survey data from the Covid-19 period and show that WFH had a mitigating role on the negative pandemic impacts which disproportionally fell on women regarding increased house- and child-care duties and job losses. Angelici and Profeta (2020) conducts a randomized control trial on a sample of 310 employees in a large Italian company, finding stronger appreciation among women for the benefits of remote working in terms of work-life balance. Nagler *et al.* (2024), leveraging a state choice experiment on a sample of German workforce in 2022, show that WFH attenuates the gender pay gap in the willingness to pay to avoid commuting, which is a source of labour-market and income inequalities as women's higher reluctance to commute prevents them from catching job opportunities. By characterizing our analysis by gender and childcare service, we contribute to this literature both by going beyond the pandemic emergency – a period when disentangling the WFH effects from the broader impacts of the pandemic is particularly challenging – and by arguably featuring a higher external validity as our data include a much broader range of WFH workers.

The remainder of the paper proceeds as follows. Section 2 deals with data sources and shows some descriptive evidence. Section 3 describes the empirical strategy and provides evidence in support to its validity. Section 4 reports and discusses the main results and their robustness. Section 5 investigates the heterogeneity of the effects with respect to remote workers' and LLMs' characteristics. Finally, Section 6 concludes.

2 Data and descriptive analysis

2.1 Data

Our unique dataset on the universe of WFH workforce is based on the information form the official notifications submitted by Italian firms regarding employees who are working remotely. In Italy, this is a legal obligation established by law for insurance purposes with INAIL (the National Institute for Insurance against Accidents at Work).[4] Data are available at a very granular geographical level such as the municipality. This makes it possible to construct an indicator at the local labour market level (LLM), the most granular territorial level for which data on labour force participation are available. Moreover, the data source include information on worker's age, gender and nationality, thus enabling to distinguish according to socio-demographic groups. Our (endogenous) explanatory variable

[4]See Crescenzi *et al.* (2022) for more details on these data and the institutional framework.

of interest is constructed by the change between 2019 and 2022 (last available year) in the number of LLM's employees that worked remotely at least one day in the year,[5] scaled by the number of employees in the LLM in 2019 (from Istat, the Italian National Institute of Statistics).[6] We consider the change until 2022 in order to overcome the emergency period, since in 2021 pandemic waves still occurred.[7]

The dependent variables refer to labour-market outcomes in terms of labour-force participation and employment, that we measure as changes in the activity and employment rates. Data about activity and employment rates come from the Labour Force Survey (LFS), a survey harmonized at European Union level and commonly used for the analysis of labour market. As LFS is a survey, there is trade-off in terms of sampling error between the geographical detail and other possible sub-classifications (e.g, by gender, by age, by sector). We take data at the highest degree of spatial granularity for which they are published, i.e., the LLM. At this geographical level, data are available only referred to the whole population aged 15 years or above.[8] This implies that we cannot directly distinguish by gender or age in our dependent variables. However, in Section 5 we exploit the information on the WFH workers to characterize our results gender-wise and age-wise. Moreover, we have to cope with the fact that the age bucket to which our dependent variables refer (15 years or more) is not the most commonly used to analyze the employment rate and the activity rate (15-64 or 20-64). To address this point, by using province-level data, we show that there is a high correlation both in level and in change between these age buckets. Moreover, in our regressions we control for the share of people aged 65 or older over the population with at least 15 years old, in order to account for the possible mechanical effect of having a higher incidence of retired people. The changes in activity rate and in employment rate are computed between 2019 and 2023, the largest time span for which data are available. In this way, we can assess an effect that goes as far as possible beyond the pandemic emergency.

Our main instrumental variable is the work-from-home-potential (WFHP) in the LLM. We start from the measurement constructed in Basso *et al.* (2022) and similar to the one developed by Dingel and Neiman (2020). This measure is based on the occupations' suitability to be performed remotely (because not requiring for most time in-person human interactions) and on the occupation-mix at a narrowly defined industry level. We map the industry level data into a LLM-level measure by weighting each industry-specific WFHP

[5]Results are robust if we consider higher thresholds, e.g.: 30, 50 or 100 days per year. These estimates are not shown for the sake of space, but are available from the authors upon requests.

[6]Istat data on the number of employees in LLM are based on the Integrated System of Registers (SIR), which produces statistics from administrative data structured in statistical registers and integrated with survey data (Ascari *et al.*, 2023).

[7]In Section 4.2 we show that results are robust to the use of 2019-2021 changes.

[8]Istat reports the associated sampling error of the published data. Since the sampling error is typically higher for the unemployment rate, we do not consider this variable in our analysis.

using as weights the industry's share of the LLM employment in 2019. Since our data on the employment mix in the LLM are at most at the 3-digit level, we collapse sub-industries within any given 3-digit industry using as weights their share in that 3-digit industry at the country level.[9]

As more thoroughly discussed in Section 3, our identification strategy relies on the *conditional* validity of the instrument, whereby we have to control for covariates that correlate with both the distribution of the instrument and the dependent variables. These variables, which are described more in detail in Section 3.1, are all built from Istat data by collecting a number of sources: Census data, administrative registries, LLM classifications, etc.

2.2 Descriptive analysis

The increase in WFH was heterogeneous across the Italian territory (Fig. 1). In the Northern part of the country it was much more widespread than in the South. However, even in the South there are some areas that showed a non-negligible increase. Another stylized regularity appearant from Fig. 1 is that metropolitan areas are more heavily involved in WFH. This is likely connected with their higher share of occupations in the service sectors performed by highly skilled people, which are generally more suitable for remote working. The patterns are similar for men and women, but we can notice that Southern areas displaying a more intense color are generally on the female panel. In all the four Italian macro-areas, the diffusion of WFH is somewhat larger on average among women than men, but only in the South the mean-difference is statistically significant in a mean comparison test (Table A.1 in the Appendix).

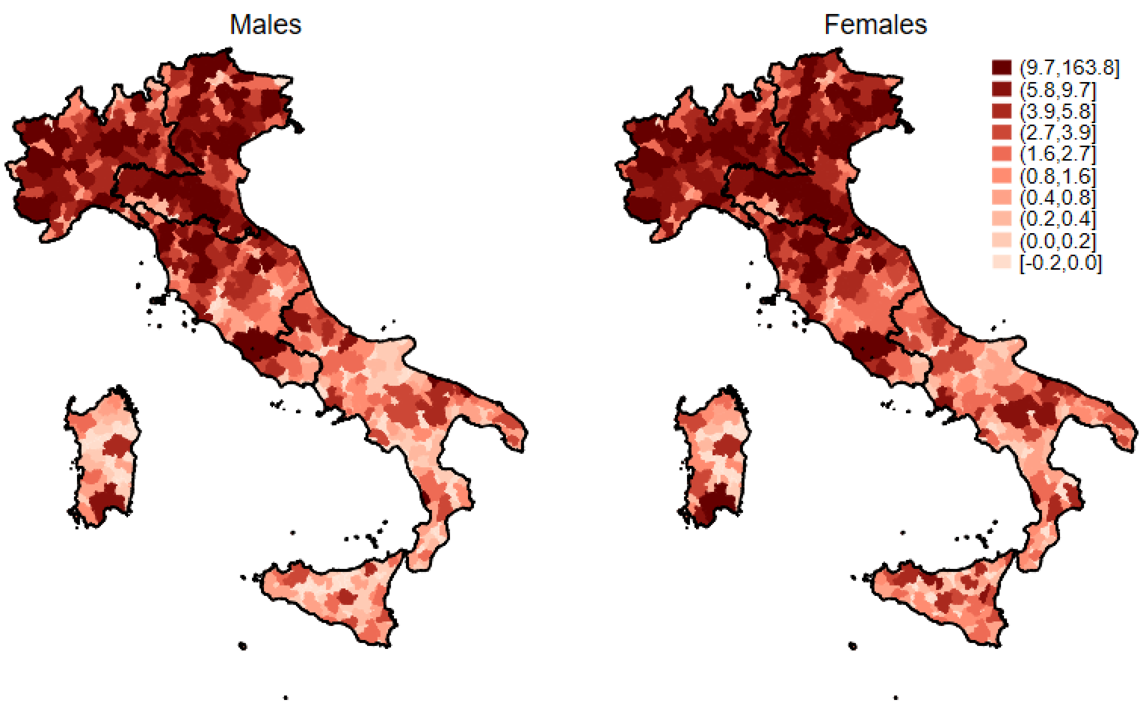
The post-pandemic recovery in Italy was employment rich, driven by the service sectors (Banca d'Italia, 2024). Also the participation rate in 2023 reached an average values above the one in 2019. Southern areas – where employment and activity rates are both structurally lower than in the rest of country – exhibited on average a larger increase, thereby partly reducing the gap with the North (Figure 2).

For the purposes of our analysis on the role of WFH, this descriptive evidence underlines that there could be confounding factors that need to be controlled for in order to avoid spurious correlations. A first-glimpse comparison of Figures 1 and 2 would suggest, if any, a negative unconditional correlation, which would be wrong though to interpret as causal.[10] We discuss this issue more in detail in Section 3.

[9]In Section 4.2, we show that the results are robust if we use a similar variable built from Dingel and Neiman (2020)'s data. Basso *et al.* (2022) and Dingel and Neiman (2020) follows a similar approach starting from the information in the US Department O*NEt survey. For our purposes, the main advantage of using Basso *et al.* (2022) is that it crosswalks occupation definitions into the European standard and provides a narrowly defined measurement at the sector level based on actual Italian data from the European harmonized Labour Force Survey data, the same source of our labour-market outcomes.

[10]The negative unconditional correlation, however, is not statistically significant.

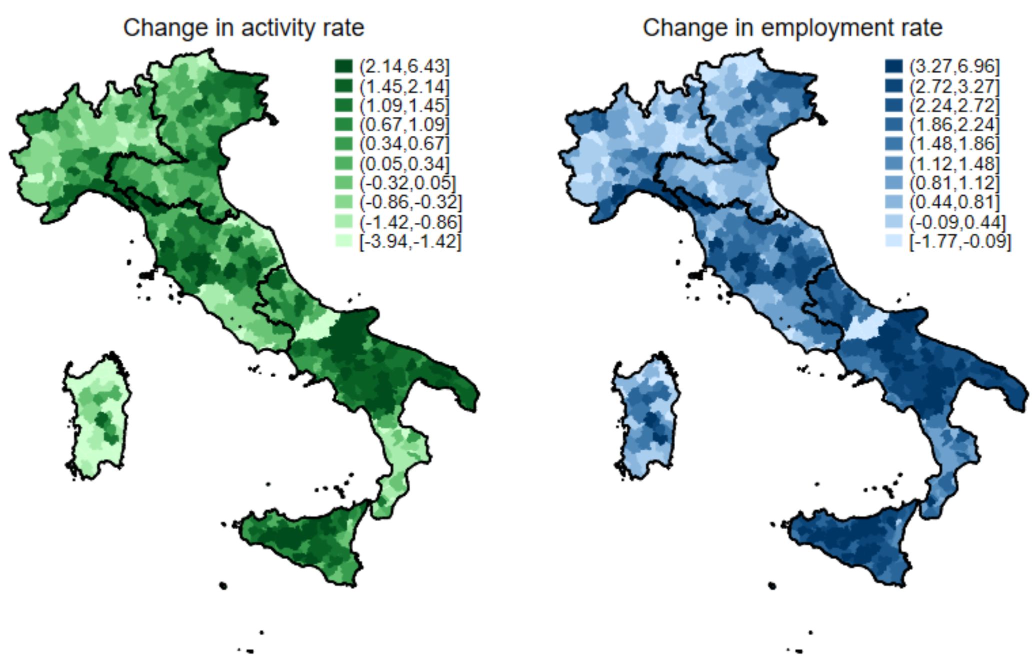
Figure 1: Increased diffusion of WFH



The figure reports the change between 2019 and 2023 in the number of employees in the 15-64 years old age group with at least one day of WFH in the year. Data are scaled by the total amount of employees of the same gender in 2019 and are reported on a per cent basis. Deciles are defined over the overall distribution of both genders.

As stated in Section 2.1, the LLM data on labour market outcomes refer to the entire population of individuals aged at least 15 years. In order to support the validity of our analysis, we show that: (i) the aggregate changes at the macroarea level implied by the LLM data are consistent with the official aggregate data at such level (Table A.2 in the Appendix); (ii) there is a very strong correlation in the province-level data between the dynamics of the 15-to-89 years bucket and the 15-to-64 years bucket (which is the most commonly used for activity and employment rates), as reported in Table A.3 in the Appendix.

Figure 2: Labour market participation and employment rates – 2019-2023 percentage point changes



Data refer to the LLM population of at least 15 years of age and time variations are taken over the 2019-2023 interval.

3 Empirical model and identification strategy

3.1 The baseline model

The empirical model aims to estimate the causal effect of WFH on the activity rate and the employment rate. As the diffusion of WFH has increased substantially only after the pandemic shock, we take the last pre-pandemic year (2019) as our base year and compute the changes in outcome variables with respect to that year. By taking the dependent variable in changes rather than in levels we also eliminate the unobserved time-invariant heterogeneity across LLMs affecting the level of these rates. The baseline model is as follows:

$$\Delta y_{2023-2019,i} = \alpha + \beta \Delta WFH^{a,g}_{2022-2019,i} + \gamma \boldsymbol{X}_{2019,i} + \epsilon_i \tag{1}$$

where y refers either to activity rate or employment rate; the subscript i refers to the LLM; Δ denotes the difference in percentage points between the subscripted years. The explanatory variable of interest ($\Delta WFH^{a,g}_{2022-2019,i}$) is the increase in the number of employees that worked remotely at least once in the year scaled by the number of employees in the LLMs in 2019. It is indexed by age (a) and gender (g) groups: in our baseline specification we consider both genders ($g = T$) and the 15-64 years old group (a=15-64). The vector $\boldsymbol{X}_{2019,i}$ includes a number of pre-determined or time-invariant LLM features that are going to be described below; they serve as controls for confounding factors and are necessary for the conditional validity of our instrument. Robust standard errors are considered.[11]

The estimation of Eq. (1) by OLS is unlikely to retrieve an unbiased estimate of β as it can be suspected to be affected by endogeneity issues. Though $\Delta WFH^{a,g}_{2022-2019,i}$ is taken over a shorter interval than the dependent variable to limit reverse causality, there could be omitted variables that relate to both the use of work-from-home and the labour market performance in the LLM. For example, demographic factors about the population composition could affect both the labour supply and the workers' demand for remote working. Moreover, unobserved differences in firm characteristics (e.g., managerial ability; see Lamorgese *et al.*, 2024) could affect both firms' attitude towards remote working arrangements and their demand in the labour market.

Taking these challenges into account, we employ an instrumental variable strategy utilizing an instrument that cannot be altered in the short run and leverages the exogenous nature of the COVID-19 shock. More in detail, following Alipour *et al.* (2021), we consider as instrument a measure of work-from-home-potential (WFHP). As described in Section 2, we borrow such a measure (defined at a narrow sectoral level) from Basso *et al.* (2022) and map it into a LLM-varying variable, according to the predetermined sectoral shares of employment. More formally, the instrument at the LLM level is constructed from the industry level data as follows:

$$WFHP_i = \sum_{j=1}^{J} WFHP_j \omega_{i,j}$$

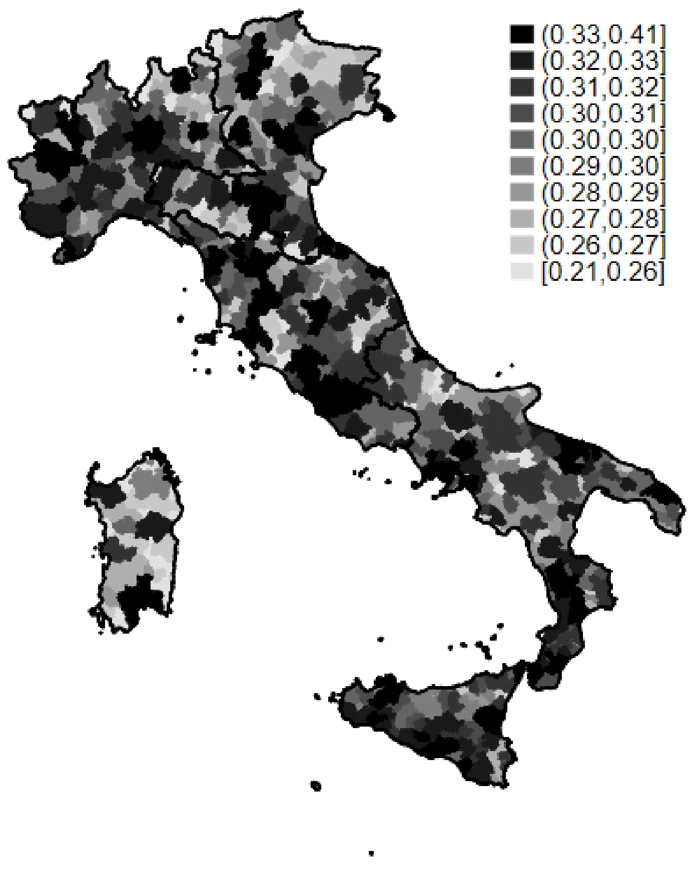
where $WFHP_j$ denotes the work-from-home-potential measured according to Basso *et al.* (2022) in the 3-digit industry j and $\omega_{i,j}$ is the employment share of industry j in LLM

[11] In specifications involving multiple observations per LLM – as in the event-study analysis presented in Section 4.2 – standard errors are clustered at the LLM level. However, since model (1) is a cross-section, clustering at the LLM level would be equivalent to employing robust standard errors. In Section 4.2, we also conduct a robustness check in which standard errors are clustered by LLM's main sector.

i. Both $WFHP_j$ and $\omega_{i,j}$ are taken in 2019. In a robustness check, we also consider an alternative instrument where the WFHP is based on the Dingel and Neiman (2020)'s data and mapped into the LLM level in an analogous way.

At the onset of the Covid-19 pandemic, each LLM featured a different average WFHP depending on the sectoral distribution of its economy, in a way that cannot be easily manipulated in the short run and that does not depend on the specific firm's characteristics (or does so to a negligible extent). As the Covid-19 pandemic was an unexpected massive shock that induced a considerable shift toward remote working, LLMs were exogenously exposed to this shock at a different degree (Fig. 3). Since the use of WFH also endured after the pandemic with a certain persistence (Crescenzi *et al.*, 2022; Basso *et al.*, 2025), this heterogeneous shock has not impacted the labour market only during the pandemic peaks but also afterwards.

Figure 3: WFH potential



The figure reports the distribution of the instrumental variable given by the WFH potential based on the measure developed by Basso *et al.* (2022) and constructed at the LLM as described in the text.

However, even if WFHP is more exogenous than actual WFH, there are still threats to identification due to the non-random distribution of $WFHP$ across LLMs, which is likely correlated with other factors influencing labour market outcomes. Think for example to service versus manufacturing oriented LLMs: several service sectors involve a higher number of occupations whose tasks are suitable for remote working; at the same time, several manufacturing industries may be on a declining secular trend. This may induce a positive spurious correlation between $WFHP$ and the labour market outcomes. Also the firm structure may introduce a confounding factor as the average firm size varies across sectors (and so with respect to $WFHP$ too) and smaller firms – which are not evenly distributed – could be in different employment trends than larger firms.[12] Another possible confounder related to the sectoral distribution is the different exposure to international demand (higher in the tradable-good industries), which could have its own effect on labour-market outcomes while being correlated with $WFHP$. Taking all these considerations into account, we include in $\boldsymbol{X}_{2019}$: the share of workers in manufacturing industries; the share of workers in larger firms (250 or more); the share of workers in smaller firms (less than 10 workers); classes of export intensity (based on quartiles of export per-capita). All these variables come from Istat data.

Moreover, demographic characteristics can affect labour market outcomes and $WFHP$. For example, more educated individuals – who are more present in some areas – tend to have a stronger attachment to the labor market and are also more likely to work in occupations that are better suited for remote work. Another relevant instance concerns the female workforce: since in Italy the female participation to the labour force is low compared to the other E.U. countries, any catching-up process could make labour-market trends correlated with the gender composition, which in turn is likely correlated with $WFHP$ due to the uneven distribution of female workers across sectors. Moreover, factors related to age can also play a role: e.g., older workers could be more attached to in-presence work and their labour supply may differ from that of younger individuals. In addition, controlling for the incidence of the elderly population is particularly important given that our participation variable is available for individuals aged 15 or more (see Section 2).[13] Based on these considerations, we include in $\boldsymbol{X}_{2019}$: the share of population with tertiary education (Census data); the share of population aged 65 or more (Census data); the employees' average age; the share of female employees; and the employment share of sectors where female workforce is more prominent.[14]

[12]In the analysed period both employment and activity rates are positively correlated with the share of small firms. Hence, not controlling for this could introduce a positive spurious correlation.

[13]Notice that, from a theoretical viewpoint, factors directly affecting workers' demand for WFH and labour market outcomes would not be an issue since our instrument relies on technical factors. However, accounting for the above-mentioned factors is appropriate for the instrument's conditional validity because of compositional reasons as long as the territorial distribution of $WFHP$ can be correlated with them.

[14]We compute the employment share of sectors where female workforce is more prominent as the share of 1-digit sectors where the incidence of female workers is above its average incidence across all sectors (at the country level).

We take into account that also economic-geography characteristics of the LLM can correlate with the distribution of $WFHP$. For example, consider the LLM type: urban or highly populated LLMs may take advantage of agglomeration economies, thereby being on different labour-market trends, and occupations that are more WFH-friendly are more prevalent in urban areas (Althoff *et al.*, 2022). Moreover, the structural North-South divide in Italy that involves several socio-economic aspects (Accetturo *et al.*, 2022a) could correlate with both $WFHP$ and labour market outcomes. Taking these elements into account, we include in $\boldsymbol{X}$: the log of resident population; a set of dummy variables for the LLM type in 5 classes (unspecialized, urban, specialized in "Made in Italy" manufacturing, specialized in "heavy" manufacturing industries, other non-manifacturing LLM) based on Istat classification; a dummy for South.[15]

Whenever the control variables included in $\boldsymbol{X}$ are time varying, we take the 2019 value or an average over earlier years. Table A.4 provides summary statistics.

3.2 Instrument validity

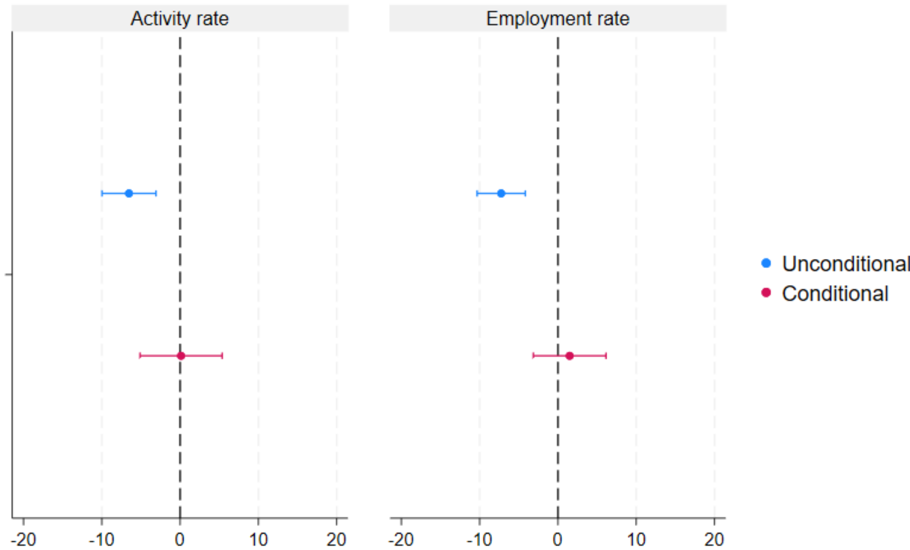
In this Section we provide some evidence in support of the validity of $WFHP$ as an instrumental variable to identify β in model (1). As mentioned in Section 3.1, validity is meant as conditional validity – i.e., conditional on a set of control variables – since the distribution of WFHP is not random across characteristics that may themselves affect labour market outcomes during the period under analysis. This is important also for the exclusion restriction. Among possible sources of endogeneity, the most serious concern regards the presence of omitted variables on top of our set of controls. In this respect, it has first to be noticed that we do estimate the model in changes, rather than in level, thus removing any time-invariant unobserved heterogeneity. It is however possible that the instrument still correlate with some uncontrolled trend in the dependent variable. In order to put this issue under scrutiny, we run a pre-trend falsification test, whereby we check whether the instrument has any predictive power on previous changes of the dependent variable: should this be the case, validity concerns would arise.

In particular, we run the reduced-form regression considering the 4-year period change (same time span as in the baseline specification) between 2015 and 2019 in the dependent variable ($\Delta y_{2015-2019,i}$). Figure 4 (and Table A.5 in the Appendix) shows that the instrument is correlated with the prior trend of the outcomes when we do not condition on $\boldsymbol{X}_{2019,i}$, whereas no such correlation emerges when conditioning on this set of controls.

In order to further examine the conditional validity of our instrument, we allow the pre-trend window to vary by up to 2 years in either direction relative to the baseline span.

[15]We considered a more granular set of dummy variables for each of the main four Italian macroareas (thereby splitting Centre-North into North-West, North-East and Centre), but we find that results are substantially unaffected.

Figure 4: Pre-trend test: unconditional and conditional estimates



The plots report the reduced-form estimates where the time change in the outcome variable is taken between 2015 and 2019. Confidence intervals at 95% significance level based on robust standard errors are reported. Estimates are also reported in Table A.5 in the Appendix.

Figure A.1 in the Appendix shows that, across all time spans, conditioning on our set of control variables removes the correlation between the instrument and prior outcome trends at the conventional 95% significance level.[16]

The second requirement for the instrument's validity regards its relevance: the instrument has to be predictive of actual WFH in the period of interest (2019-2023) conditional on controls. Evidence in support of that is provided by the first-stage regression, which shows a highly significant coefficient for $WFHP$ in explaining the increase in the actual use of WFH.[17] Table 1 shows the first-stage results for various groups defined by gender and age, with the first column referring to the baseline specification (both genders and conventional active age). The instrument has a strong predictive power in all columns.

The identification also relies on the assumption of monotonicity: the effect of the instrument on the endogenous variable has to go in the same direction for all units. We provide evidence in support of this assumption by splitting the sample in two subgroups according to whether $WFHP_i$ is below or above its median value: for both groups the sign of the instrument is strictly positive (Table A.7 in the Appendix). Moreover, we find that the higher the value of the instrument the higher the positive effect. We repeat the same exercise for the group of only men and only women and the results are substantially

[16] For each outcome variable, in one time span out of five there is a 90% significance: the 2013-2019 period for the activity rate and the 2015-2019 period for the employment rate. See Table A.6 in the Appendix.

[17] When presenting the main results from the 2SLS estimator in Section 4, the reported robust F-statistic is always scores above 10, the conventional value below which the instrument can be suspected to be weak.

Table 1: First stage regression

	(1) $\Delta WFH^{15-64,T}$	(2) $\Delta WFH^{15-64,M}$	(3) $\Delta WFH^{15-64,F}$	(4) $\Delta WFH^{25-49,T}$	(5) $\Delta WFH^{25-49,M}$	(6) $\Delta WFH^{25-49,F}$
WFH potential	91.737**	85.928**	99.414**	56.964**	49.709**	66.416**
	(19.560)	(17.895)	(23.207)	(12.740)	(10.488)	(16.651)
Controls	Y	Y	Y	Y	Y	Y
F	18.285	19.231	15.204	17.83	19.706	14.474
R^2	0.350	0.434	0.257	0.289	0.399	0.201
Obs	606	606	606	606	606	606

The table refers to OLS coefficient of the instrument in the first-stage regressions where the dependent variable is the change in actual use of WFH between 2019 and 2022 among workers of sex and age-class indicated in columns (T, M and F indicates respectively total, male, and female). The regressions include the set of control variables specified in model 1. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

confirmed.[18]

Other typical sources of endogeneity are reverse causality and measurement errors.[19] The former seems a minor threat for our instrument as the Covid-19 shock was unexpected and the WFHP was predetermined by the economic structure of LLM that could not be altered at a short notice. Furthermore, we have shown that there is no conditional correlation of our instrument with pre-trends of the dependent variables. With regard to measurement error, it may arise in our context either from the sampling error inherent in the dependent variables (which we address in Section 4.2) or if workers usually work remotely from another LLM. While the latter circumstance might occur, it regards a minority of remote workers, also considering that the most common forms of WFH are hybrid arrangements that requires some on-site presence per week.[20] Moreover, even if such measurement errors were present, they would need to be systematic in order to introduce bias, and it is difficult to see why this should be the case. Instead, non-systematic measurement errors would, at most, result in an attenuation bias in our estimates, ensuring that at least lower bounds are identified.

Another possible concern with this identification strategy may be linked to the recent literature on shift-and-share instruments (Goldsmith-Pinkham *et al.*, 2020; Borusyak *et al.*, 2021, 2025), that highlights the importance of analysing whether the identification comes through the shifts or the shares. The former vary at a different level than the unit of analysis (say $j \in J$), whereas the latter map the former into the dimension of the unit of analysis (say, $i \in L$). Although in the canonical Bartik-style instrument shifts are rep-

[18] For some regressions on the sample of LLMs with lower potential the statistical significance is not achieved given the large standard errors but the positive sign and increasing gradient are confirmed.

[19] Another potential source is correlated shocks. During the period under analysis, a significant shock was the resurgence of inflation. Although inflation data are not available at the LLM level, an examination of province-level data reveals that the correlation between the increase in prices and the increase in activity (or employment) rates is low and not statistically significant.

[20] Based on *Labour Force Survey* data, only 8% of remote workers exclusively work from home. Moreover, almost 85% of individuals who engage in any form of WFH have their workplace located either in their municipality of residence or in another municipality within the same province. For less than 5% of them the workplace is outside region.

resented by variations over time, the analytical framework developed by Borusyak *et al.* (2025) is not necessarily limited to that case. In our context, the j dimension refers to the industries for which the WFHP is available at the national level and the units of analysis, onto which the shares map the industry-specific potential, are the employment shares. Both WFHP and shares are predetermined, but the identification could be less credible if it occurs only through the employment shares as they could be associated to many uncontrolled or unobserved shocks. When the J dimension is large enough, the identification can be supported by an analysis at this level (Borusyak *et al.*, 2025). In our framework, we can leverage a sufficiently large number of industries (245) as they are defined at the 3 digit level. They meet the requirement of being sufficiently diversified: the inverse of the Herfindahl index of industry weights at the country level scores at 71.6, sufficiently high according to the Montecarlo simulations in Borusyak *et al.* (2021) who report that 20 can be enough to have a good asymptotic approximation. The largest industry's share is also sufficiently low (4.6%).[21] Our instrument also reasonably meets the requirement that the exposure cannot be strategically manipulated since WFHP is measured on the (predetermined) task content of occupations and it is based on the sectoral distribution of occupations before the unexpected Covid-19 shock. As far relevance is concerned, Fig. A.2 in the Appendix shows that also at the "shift" level (i.e., industry level) there is a strongly significant positive correlation between the WFH potential and the increase in the actual use of WFH, irrespective of whether industries are weighted by their workers. Moreover, in Table A.8 in the Appendix we show that a positive first-stage relationship also holds on the shift-level equation of model 1 after residualizing and aggregating variables as described in Borusyak *et al.* (2021). Positive and significant effects at the shift levels are also detected in the reduced form models (Table A.8).

4 Main results and their robustness

4.1 Main results

We first consider the reduced-form regression. The results reported in Table 2 show that the instrument significantly explains the change occurred in each of the considered outcomes. Combined with the evidence provided in Section 3.2 this means that, conditional on covariates, the instrument (the WFH potential) has no explicative power on prior trends of the dependent variable (activity or employment rate) but it has in the period of interest.

We can now move to the main research question, i.e., whether the increase in the use

[21] Our framework seems to fit the situation "when most regions specialize in a small number of industries, differentially across a large number of industries." (Borusyak *et al.*, 2021, , p. 191).

Table 2: Reduced form

	(1) Activity rate Change 2019-2023	(2) Employment rate Change 2019-2023
WFH potential	10.600**	7.942**
	(3.052)	(2.554)
Controls	Y	Y
Obs	606	606
R^2	0.273	0.450

The table refers to OLS estimates of the change in activity and employment rates between 2019 and 2023 on the instrument. The model includes the set of control variables included in model 1. Robust standard errors in parentheses; $^+$ $p < .10$, * $p < .05$, ** $p < .01$

of WFH following the pandemic shock has brought about in the medium run any effect in labour-market participation and employment. In Table 3 we show the OLS and 2SLS results for β in model (1), adding the robust F-test for instrument's power for the latter estimator.

Table 3: WFH impact on participation and employment rates

	Activity rate		Employment rate	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
β	0.023**	0.116**	0.019***	0.087**
	(0.004)	(0.041)	(0.004)	(0.033)
Controls	Y	Y	Y	Y
R^2	0.270	0.089	0.449	0.342
Obs	606	606	606	606
Rob. F-stat		21.996		21.996

The table reports OLS and 2SLS estimates for β in model (1), where $a = 15-64$ years old and $g = T$, i.e. both genders. The change in the use of WFH is computed over 2019-2022, while the change in the dependent variable is in the 2019-2023 period. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^+$ $p < .10$, * $p < .05$, ** $p < .01$

The IV results in Table 3 implies that *ceteris paribus* one percentage point (pp) increase in the explanatory variable (ie, the per cent ratio of WFH increase over the initial stock of LLM employees) has brought about an increase in the activity rate by 0.12 pp and an increase in the employment rate by 0.09 pp in the local labour market. Both estimates are statistically significant at 1% and higher than their OLS counterparts which may be biased because of the various forms of endogeneity discussed in Section 3. This means that a simple OLS estimation, though applying a multivariate framework and detecting a positive effect, would still lead to a substantially underestimated impact of WFH in spurring participation and employment.

The results are consistent with the evidence in the literature of a positive evaluation of WFH by workers, who appreciate the savings in commuting time/costs and the higher flexibility to balance private- and work-life duties (Cullen *et al.*, 2025; Aksoy *et al.*, 2023b; Barrero *et al.*, 2021; Nagler *et al.*, 2024). Our findings suggest that these gains have an impact on the extensive margin, by inducing ceteris paribus some individuals to enter the labour market while they otherwise would have not. Although the magnitude of the impact on employment is lower than on participation, it is still positive and significant, suggesting that the increased labour supply has also, at least partly, translated into employment.

The estimates are significant also from an economic point of view: a one standard deviation increase in the explanatory variable is associated to a rise by 0.9 pp in the activity rate and 0.7 in the employment rate.[22] When we consider the interquartile difference, results are somewhat smaller, but still sizeable: 0.5 pp and 0.4 pp on the activity and employment rates, respectively. Compared to a situation with no change in remote working (ie, $\Delta WFH_{2022-2019} = 0$), the average value taken by the explanatory variable is associated to almost 0.5 pp rise in the activity rate and almost 0.4 pp in the employment rate., corresponding respectively to about one third and one fourth of the standard deviation of the dependent variable.

While these quantitative exercises results are informative for comparing LLMs, one has to be cautious in extending them to aggregate figures since estimates are unweighted, i.e., every LLM is equally weighted. If LLMs are weighted by the local population, no significant impact emerges (Table A.9). This suggests that the effect might be non-homogeneous across LLMs, an issue that is specifically addressed in Section 5.3.

4.2 Robustness

We check the robustness of our results in several respects. First, we provide further support to our instrument by addressing other possible threats to identification and by considering an event-study framework. Second, we assess how sensitive the results are to the choice of the instrument. Third, we exclude from our instrument the ICT industries, which features both a high level of WFH potential and positive employment dynamics in aggregate in the analysed period. Fourth, we cluster standard errors to explicitly account for the correlation in exposure among LLMs that have the same main sector in common. Fifth, we consider whether results are robust to taking the change in WFH over a different (shorter) time period. Sixth, we run the baseline model after excluding outliers from the

[22]These respectively correspond to about two thirds and one half of the sample standard deviation of the dependent variable

sample. Seventh, we check whether and how results are affected by LLMs featuring a higher sampling error.

In Section 3.2 we have provided evidence in support of our instrument's validity conditional on a set of controls. However, there could be other factors, not included in that set, that could bias the estimates. For example, as mentioned in Section 2.2, the post-pandemic labour market recovery in Italy was higher in lagging behind areas, so that we observe a negative correlation of our outcome variables with initial productivity, population density and share of foreign people (which is usually higher in zones with more job opportunities). If – despite conditioning for our set of controls – these variables turns out to be correlated with our instrument, estimates might be biased. In Table A.10 in the Appendix we formally check that by conducting a falsification test where we run reduced-form models considering the following placebo dependent variable: the initial population density (in logs), the initial share of foreign population, and a dummy for more productive LLMs (based on predetermined average labour productivity in the LLM computed by Istat). None of the coefficient is statistically significant, pointing that if any unconditional correlation exists with our instrument it is netted out by the included controls: for example, we control for the LLM's urban class and size and this appears to have already caught the possible confounding role of densely populated LLM.

In Section 3.2 we have tested pre-trends conditional on our set of controls. We now report a further exercise whereby we recast our model in an event-study framework: we consider as treated the LLMs where the instrument is above its median and estimate a panel model with LLM fixed-effects and years fixed-effects (taking 2019 as the last observation before the event) and where the dependent variable is the level of activity or employment rate. In this setting, controlling for our set of covariates amounts to allowing for varying trends based on these variables. Operationally, we interact a linear trend with dummy variables defined by the controls' values when they are discrete and by classes based on quantiles of their distribution when they are continuous. Figure A.3 shows that the conditional specification is substantially able to remove or attenuate pre-trends (i.e.: coefficents are not statistically significant in the pre-event periods, even if for the activity rate this occurs at a borderline level at the second lead), while highlighting a clearly positive post-event impact, which is both significant and increasing over time.

In our preferred specification the IV strategy uses the measurement of WFH potential in Basso *et al.* (2022). As this measurement slightly differs from Dingel and Neiman (2020), a first robustness check aims to assess whether the results change when basing our instrument on the latter. Moreover, we also consider an alternative instrument, not related to sectoral WFHP, but based on the average speed of broadband connection in the LLM in 2019, with the underlying intuition being that WHP is easier to implement in areas where workers and firms can benefit from a faster internet connection (Basso *et al.*, 2025). Similarly to WFHP, also the broadband speed is not randomly distributed and potentially correlated with prior trends in the dependent variable if we do not condition on a set of control variables. In Table A.11 in the Appendix, we show that both alternative instruments are uncorrelated with the change in the dependent variables in the 4-year period preceding the analysis, whereas they exhibit a positive correlation in the 2019-2023 interval (reduced form). Table A.12 in the Appendix shows that the 2SLS estimation using the Dingel and Neiman (2020)-based instrument yields impacts that are pretty similar in magnitude to those reported in Table 3, albeit with a lower level of statistical significance (5%). Though still above 10, also the robust F-test statistic is lower than in our preferred specification.[23] Also the estimates using the broadband-speed instrument point to a positive effect, which appears to be even larger in magnitude than in our baseline result (with a 5% significance). However, in this case the F-statistic falls slightly below 10, suggesting that there could be an issue of IV-weakness. Based on this evidence, we can observe that the findings about the positive effect of WFH are not reversed under alternative instrument and, at the same time, the baseline specification can be maintained as the preferred one.

In the next robustness check, we consider our baseline instrument but construct it excluding the ICT industries, which are characterized by both a high potential for remote work and positive employment dynamics during the period under analysis.[24] Due to these characteristics, the robustness of our results would be called into question if they were solely driven by this sector. However, we find that it is not the case as our results are robust to the exclusion of the ICT sector from our identification: Table A.13 shows that this holds for both the reduced form – as evidenced by the absence of pre-trends and the presence of a positive effect during the period of interest – and the 2SLS estimates, where the coefficients for both activity and employment rates are, if any, even larger than those reported in Table 3.

In the next robustness check we take into account that the shock exposure of LLMs specialized in the same sector can be mechanically correlated if this sector has a remarkable weight in the LLMs' economy. We address this issue by clustering the standard errors at the main industry, similarly to Berton *et al.* (2018). As shown in Table A.14 in the Appendix, notwithstanding the larger standard errors, the coefficient of the two stage least square models are still significant at the conventional 5% level. This suggests that our findings are robust to the structural correlation of disturbances operating through sectoral compositions.

[23] This likely occurs because the Dingel and Neiman (2020)-based instrument has a lower variability than the Basso *et al.* (2022)-based instrument.

[24] According to national accounts data, the employment growth rate in ICT industries between 2019 and 2022 (the most recent year available) was more than twice as high as the overall employment growth rate.

As a further robustness check, we test how sensitive are our findings to the time span over which we compute the increase in remote working. In fact, our explicative variable is measured as the change between 2019 and 2022, which is the most recent year for which we have data for the whole year. We now consider the difference between 2019 and 2021. If the effect that we have found in the baseline specification was casual (due to some idiosyncrasies in 2022) it should disappear under this specification. Table A.15 in the Appendix replicates Table 3, but β now refers to $\Delta WFH_{2021-2019,i}$. The estimates are pretty similar to those in Table 3, both in terms of magnitude and statistical significance, thus suggesting that the territorial heterogeneity in the increase in WFH is somewhat persistent and so its effect is robust to changing the time span.

Next, we investigate if and how much results are sensitive to outliers. We define outliers as values below the first percentile or above the 99th percentile. Table A.16 in the Appendix reports the baseline results on the whole sample (col. 1 and 4 for the activity and the employment rate, respectively) followed by estimates on subsamples that exclude outliers in the dependent variable (col. 2 and 5) and in the WFH explanatory variable too (col. 3 and 6). When we remove LLMs with more extreme variations in participation (col. 2), the impact remains positive and just slightly lower. When also the LLMs with more extreme variation in WFH are removed from the estimation sample (col. 3), the point estimate gets higher. To replicate the back-of-envelope exercise in Section 4, we associate this coefficient to the (lower) standard deviation increase in this sample and find that it brings about an impact of 0.8 pp, very similar to what found in Section 4.1. As regards the employment rate, we again observe a reduction when only the outliers in y are excluded, with the coefficient remaining positive and significant; when also outliers in WFH are removed, the coefficient's magnitude is similar to the baseline, albeit only 7% significant. The implied impact of a one standard deviation increase in the last estimation sample can be computed at 0.4 pp, lower than the corresponding one in Section 4.1 but still sizeable. Based on this evidence, we can conclude that the main findings are not driven by outliers.

Finally, we address the concern that results might be driven by LLMs with higher sampling errors. By exploiting the information published by Istat on the sampling error associated to the estimates, we exclude from the estimation sample the LLMs in the highest 10 per cent (more than 60 LLMs) of the sampling error distribution. The results, reported in Table A.17 in the Appendix are very similar to the baseline.

5 Heterogeneity and Mechanisms

In this Section we explore heterogeneity in our results, as it can offer valuable insights into the mechanisms driving them. Specifically, we focus on heterogeneity with respect to demographics of the workers and the characteristics of the territories.

5.1 Heterogeneity by gender and age

In order to characterize our results by gender and age groups, we can distinguish the use of WFH by these dimensions, while we cannot directly assess a specific measurement of labour market outcomes by sex and age (since this information is not available at the LLM level). More specifically, we can compare the effects implied by the increased use of WFH for men and women, as well as for the 15-64 age group and the 25-49 group. The latter age group is interesting as it comprehends the stage of life in which usually child care duties are more relevant. Table 4 and Table 5 report the results for the activity rate and the employment rate, respectively.

The positive impact of WFH is confirmed to be positive and significant across all groups. Coefficients can be interpreted as the responsiveness of the total activity (employment) rate to a small and equal change in the WFH of the considered group. However, if we want to assess the actual impact on the outcomes, we cannot directly compare coefficients since the use of WFH varies across sex and age groups. Therefore, at the bottom of the Table, for each group we report the impact given by a one standard deviation change.[25]

We can observe at the bottom row of both tables that, for any given gender group, the impact is stronger in the 25-49 age class than in the 15-64 one. This hints that the participation (and employment) enhancing effect of WFH mainly occurred through the age groups that are more involved with child care duties. This naturally raises the issues whether the impact is gender-wise different since in Italy family care duties are mainly on women's shoulder. The impact on the outcome variable is higher following the increased WFH of women; this occurs for both age groups, but even more so in the 25-49 class. This is consistent with the interpretation that WFH may have partly relaxed the trade-off between work and family life.

5.2 Heterogeneity by childcare service provision

In order to investigate this issue further, we split the sample according to a proxy of the (predetermined) availability of services for childcare, such as the coverage of early-childhood care services in 2019 (i.e.: the share of available nursery places over the number of 0-2 children in the LLM). Enhancing childcare services is seen as a fundamental tool to increase both labour force participation and fertility (Carta *et al.*, 2023). In Italy there are

[25]The impact is computed by multiplying the coefficient and the standard deviation of the explanatory variable in the estimation sample. Results across groups are in general qualitatively confirmed if we consider mean or median values.

Table 4: Heterogeneity in WFH by age and gender. Labour market Participation

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta WFH^{15-64,T}$	0.116**					
	(0.041)					
$\Delta WFH^{25-49,T}$		0.186**				
		(0.066)				
$\Delta WFH^{15-64,M}$			0.123**			
			(0.044)			
$\Delta WFH^{15-64,F}$				0.107**		
				(0.038)		
$\Delta WFH^{25-49,M}$					0.213**	
					(0.075)	
$\Delta WFH^{25-49,F}$						0.160**
						(0.058)
Controls	Y	Y	Y	Y	Y	Y
N	606	606	606	606	606	606
Rob. F-stat	21.996	19.991	23.057	18.35	22.462	15.909
Std.dev-impact	**0.902**	**1.042**	**0.835**	**1.025**	**0.941**	**1.186**

The table reports 2SLS estimates for β in model (1) across different specifications for $a = \{15-64, 25-49\}$ and $g = \{T, M, F\}$. The dependent variable refers to the change in the activity rate. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table 5: Heterogeneity in WFH by age and gender. Employment.

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta WFH^{15-64,T}$	0.087**					
	(0.033)					
$\Delta WFH^{25-49,T}$		0.139**				
		(0.053)				
$\Delta WFH^{15-64,M}$			0.092**			
			(0.035)			
$\Delta WFH^{15-64,F}$				0.080**		
				(0.031)		
$\Delta WFH^{25-49,M}$					0.160**	
					(0.060)	
$\Delta WFH^{25-49,F}$						0.120*
						(0.047)
Controls	Y	Y	Y	Y	Y	Y
N	606	606	606	606	606	606
Rob. F-stat	21.996	19.991	23.057	18.35	22.462	15.909
Std.dev-impact	**0.676**	**0.780**	**0.625**	**0.768**	**0.705**	**0.889**

The table reports 2SLS estimates for β in model (1) across different specifications for $a = \{15-64, 25-49\}$ and $g = \{T, M, F\}$. The dependent variable refers to the the change in the employment rate. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

areas (e.g. the South) in which both childcare services and female labour force participation are low (Banca d'Italia, 2022, pp. 38-40).

A priori, it is not clear how the effect of WFH on labour market outcomes might change depending on the availability of child-care services. If a substitutability relationship prevails, we should expect a higher impact of WFH in LLMs where services are less present: in contexts where it is difficult to find an external provision of childcare, WFH – by allowing a better work-life balance – may encourage the labour market participation at the margin by some parents that otherwise would have not, whereas WFH can expected to be less important in stimulating participation in contexts where such services are present. Under a complementarity relationship we should expect the reverse: a stronger effect in LLMs with more childcare services, for example because WFH alone is not enough (especially if the family cannot rely on any other support) and to be effective in stimulating participation it needs to be complemented by childcare services.

Table 6: Heterogeneity by early childcare service provision

	Activity rate		Employment rate	
	lower provision	higher provision	lower provision	higher provision
	(1)	(2)	(3)	(4)
15-64 years				
β	0.490*	0.019	0.393*	0.008
	(0.222)	(0.022)	(0.179)	(0.020)
N	303	303	303	303
Robust F-stat	9.406	19.900	9.406	19.900
Std.dev.-impact	1.724	0.194	1.384	0.083
25-49 years				
β	0.721*	0.033	0.578*	0.014
	(0.351)	(0.037)	(0.283)	(0.035)
N	303	303	303	303
Robust F-stat	7.168	18.677	7.168	18.677
Sted.dev.-impact	1.894	0.238	1.521	0.102

The table reports 2SLS estimates for β in model (1) where $g = T$ and a=15-64 years (top panel) and 25-49 years (bottom panel) distinguishing between LLMs with childcare coverage in 2019 (i.e. the share of available nursery places out of the 0-2 years old population) below (or equal) and above the median. All controls in model (1) are included. Separate estimates by gender (not reported) are consistent with these and available upon request. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

The empirical evidence for Italy seems to be more aligned with the substitution hypothesis: WFH acts as a substitute for child-care services, thus concentrating the bulk of its effect in areas where the supply of such services is less widespread (Table 6). The relationship and the impact get stronger when we focus on the 25-49 group, whom parents of young children are more likely to belong to.

This does not mean that WFH is not utilized in areas with a higher childcare supply; on the contrary, it is actually more widespread in these areas. However, these findings suggest that there WFH plays a less determinant role for the extensive margin of labour market participation (and employment). In areas where the availability of childcare services is low, having the possibility of working from home can be influential in the choice of entering the labour market.

5.3 Geographical heterogeneity: macroregions and population density

The findings in Section 5.2 have potential implications also from a regional economic perspective as child-care services are not uniformly distributed (the coverage is on average higher by about 16 pp in the Centre-North than in the South). We thus explore potential heterogeneity with respect to the macroarea and other territorial characteristics.

Table 7 compares the estimates on the whole sample to those obtained for the subsample of Centre-Northern (CN) LLMs only. We cannot rely on estimates for the subsample of the South alone as its limited size does not provide sufficient statistical power of the instrument. However, the comparison between the whole sample and the CN subsample suggests that the responsiveness of participation and employment to WFH is higher in Southern LLMs, as in the Centre-North the coefficients are closer to zero and not statistically significant. This is consistent with the previous evidence of a greater responsiveness in places where childcare services are low.

Table 7: Geographical heterogeneity: Whole sample vs Centre North

	Whole sample		Centre-North only	
	Activity rate	Employment rate	Activity rate	Employment rate
	(1)	(2)	(3)	(4)
15-64 years				
β	0.116**	0.087**	0.024	0.009
	(0.041)	(0.033)	(0.023)	(0.022)
Obs	606	606	328	328
Rob. F.stat	21.996	21.996	20.876	20.876
Std.dev.-impact	0.902	0.676	0.234	0.083
25-49 years				
β	0.186**	0.139**	0.039	0.014
	(0.066)	(0.053)	(0.037)	(0.035)
Obs	606	606	328	328
Rob. F.stat	19.991	19.991	17.273	17.273
Std.dev.-impact	1.042	0.780	0.275	0.097

The table reports 2SLS estimates for β in model (1) where $g = T$ and a=15-64 years (top panel) and 25-49 years (bottom panel) distinguishing between the whole sample and a subsample made of LLMs in Central and Northern Italy only. The 2SLS uses WFH potential as instrument. All controls in model (1) are included. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Another interesting dimension for analysing heterogeneity from a regional-economic perspective regards population density, or broadly speaking more urban versus more rural LLMs. Table 8 shows that the positive effect is concentrated in LLMs where the population density is below the median,[26] a subsample that includes peripheral areas. This result is again consistent with the interpretation of WFH as an option that is more influential on labour market participation for individuals living areas with fewer services.[27] Another possible interpretation consistent with this evidence is that WFH may represent an opportunity for less densely populated area where individuals could be discouraged from entering the labour market by the time and money cost of commuting over longer distance (or the cost of moving to a more expensive city) or by family bounds. WFH may give the opportunity to attenuate this trade-off.

Table 8: Geographical heterogeneity: Population density

	Activity rate		Employment rate	
	Low density	High density	Low density	High density
	(1)	(2)	(3)	(4)
15-64 years				
β	0.162*	0.018	0.129*	0.001
	(0.077)	(0.036)	(0.063)	(0.031)
Obs.	301	305	301	305
Rob. F-stat	9.594	17.633	9.594	17.633
Std.dev.-impact	1.348	0.124	1.077	0.005
25-49 years				
β	0.269*	0.028	0.215*	0.001
	(0.128)	(0.058)	(0.105)	(0.049)
Obs.	301	305	301	305
Rob.F-stat	9.385	14.29	9.385	14.29
Std.dev.-impact	1.686	0.133	1.348	0.005

The table reports 2SLS estimates for β in model (1) where $g = T$ and a=15-64 years (top panel) and 25-49 years (bottom panel) distinguishing between the LLMs with a population density (in 2019) lower or higher than the median. All controls in model (1) are included. Separate estimates by gender (not reported) are consistent with these and available upon request. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

The finding that the effect is concentrated in less densely populated areas is consistent with the lack of significant effect on the wighted estimates, where each LLMs is weighted according to its initial resident population (see Table A.9 in Appendix, already commented in Section 4.1). If the beneficial effect of WFH in terms of labour market inclusivity is concentrated in less populated areas, it may not be apparent in macro-level figures, as it could be diluted by the negligible effect in more populated areas which have a higher weight in the aggregate.

[26]We check that the sampling error between the two sub-groups is comparable and does not differ in a statistically significant way.

[27]For example, with respect to early childcare service, the coverage is higher in more densely populated areas by almost 3pp on average, a difference which is statistically significant.

Finally, we investigate whether the LLM's specialization also plays a role. We group the LLM types in two coarser categories: manufacturing and non-manufacturing. As shown in Table A.18 in the Appendix, the estimated β coefficient is positive and rather similar in magnitude across the two groups.[28] However, the impact on the dependent variable is higher in the non-manufacturing LLMs, due to their higher utlization of WFH, which is facilitated by the easier application of remote working in service sectors' occupations.

6 Conclusions

This paper studies whether the increase in WFH following the pandemic shock has spurred labour market participation and employment. By reducing the time and cost of commuting and providing more flexibility in work organization, WFH could encourage some individuals to take part in the labour market (and potentially get employed) who might otherwise have refrained. To identify a causal impact, we adopt an instrumental variable strategy that takes advantage of the unexpected pandemic shock and the predetermined heterogeneous WFH potential, which follows from the sectoral composition of the local economy and the distribution of occupations across sectors. Since the distribution of WFH potential is non-random across the national territory, we control for a number of fixed effects and predetermined covariates that could otherwise introduce confounding factors. We show that the instrument is conditionally uncorrelated with pre-existing trends and that the results are robust to the use of alternative instruments.

We find that WFH has increased labour market participation and employment. When examining whether the effect is homogeneous, we find that a larger impact was brought about by the increase in WFH of women and of the 25-49 age group. As these socio-demographic groups are also more likely to be involved in family care duties, particularly childcare, we also address the heterogeneity with respect to the availability of early childcare services: our findings show that the positive impact of WFH concentrates in areas were these services are less present, thus suggesting that the possibility of remote working may be more influential in context where families have less external support. Our results also show that the positive impact is primarily observed in the Southern LLMs, as well as in less densely populated and more peripheral areas, where services are also less available. These impacts may not emerge in macro-level data due to the lower weight of

[28]This is also reassuring as the instrument based on WFH potential generally takes lower values in manufacturing. The IV proves to have identification power also among manufacturing-vocated LLMs, meaning that even within this group it is able to induce significant changes in the use of WFH. This is favoured by the industry-level granularity of the WFHP measure that we exploit, as well as by the fact that, even in manufacturing-oriented LLMs, there is significant sectoral heterogeneity in employment (with service sectors also contributing to this diversity).

these areas in the aggregate statistics.

Taking stock of this evidence, the encouraging effect of WFH on the extensive margin of labour supply seems to be more effective in areas where the level of labour market participation and employment is lower. This does not mean of course that WFH is not appreciated in more dynamic areas: the diffusion of WFH in fact is higher there. Rather, this suggests that in the most advanced zones WFH is less determinant for the decision of participating in the labour market, whereas it can play a more pivotal role in disadvantaged and less supplied areas. As long as the provision of family-friendly services is low, the opportunity of remote working may contribute to a more inclusive labour market.

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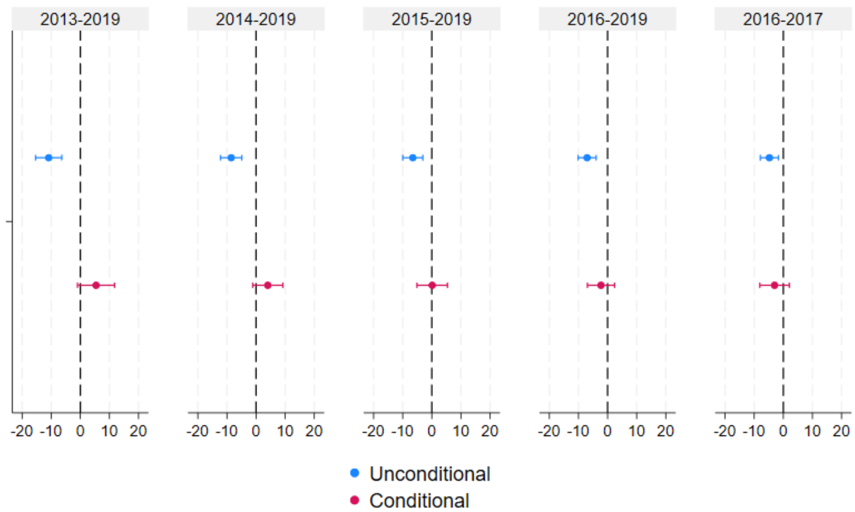
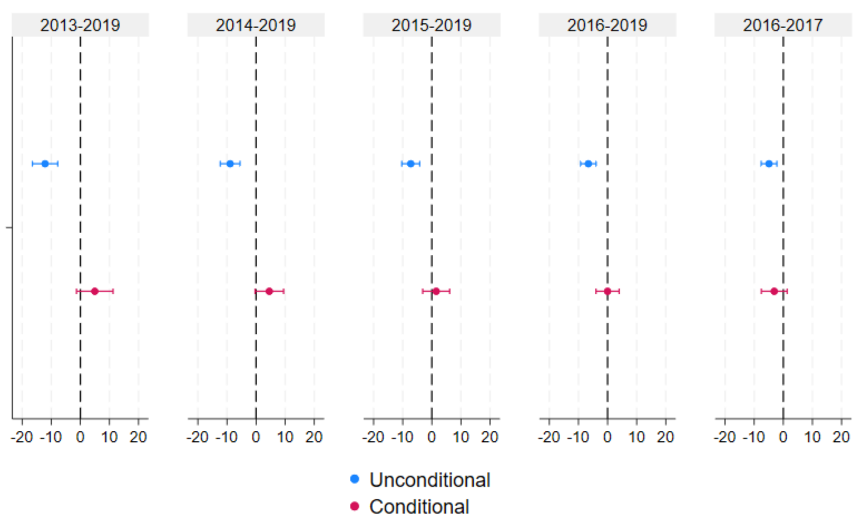
A Additional figures and tables

Figure A.1: Pre-trend test: unconditional and conditional estimates

(a) Activity rate

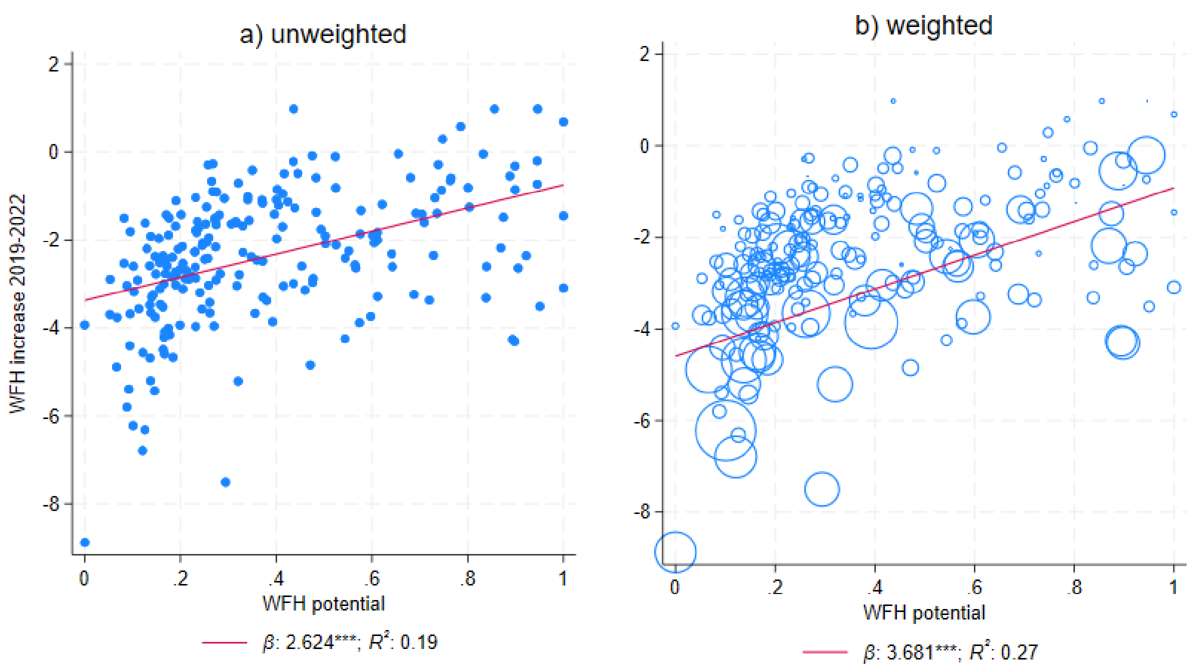


(b) Employment rate



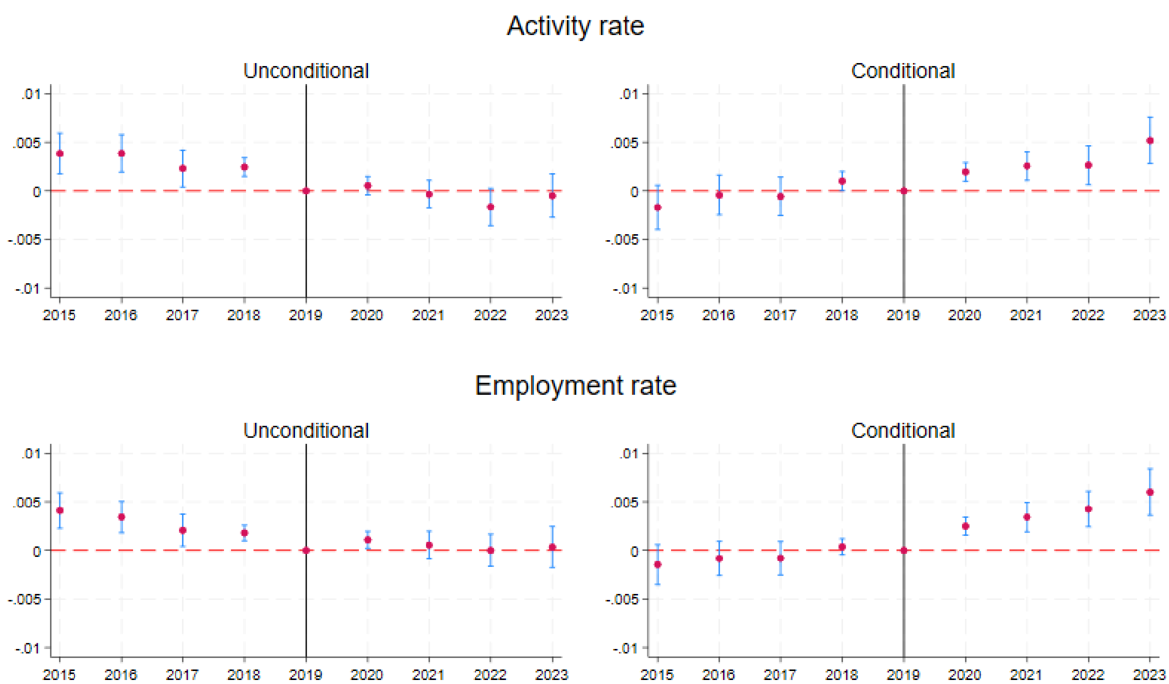
The plots report the reduced-form estimates where the dependent variable is the change between the indicated years in the activity rate (top panel) and in the employment rate (bottom panel). Confidence intervals at 95% significance level based on robust standard errors are reported. Estimates are reported in Table A.6.

Figure A.2: WFH increased use and WFH potential across industries at aggregate level



Work from home potential is based on the measurement in Basso *et al.* (2022) and computed at the 3-digit sector level as described in Section 2. The increase in use WFH is measured as the difference between 2019 and 2022 in the number of employees with a WFH experience, scaled by the number of industry workers in 2019 and reported in logs. The fitting line is based on a linear regression, unweighted in panel a, and weighted by industry's workers in panel b.

Figure A.3: Event-study application of WFH potential



The figure reports the estimates of an event-study specification with LLM and year fixed effects where the last pre-event year is 2019. The dependent variable is either the activity rate or the employment rate. The treatment is assigned if the work from home potential (measured in 2019) is above its median value. The "conditional" specifications include heterogeneous linear trends according to the values taken by our set of control variables (continuous variables are factorized according to quantiles of their distributions). Confidence intervals at 95% are based on robust standard errors clustered at the LLM level.

Table A.1: Increase in WFH by gender and macroarea

Area	Female	Male	Difference
North-West	6.53	5.75	0.78
North-East	9.31	7.92	1.39
Centre	4.75	4.25	0.49
South and Islands	1.39	0.89	0.50**
Italy	4.41	3.68	0.72

The table reports the average increase in WFH by gender and macroarea. This is measured as the 2019-2023 change in the number of employees with at least 1 day in WFH every 100 employees of the same gender in 2019. The average is taken as the unweighted average over LLMs in the macroarea. Legend: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Macroarea values implied by LLM data and aggregate values

	Activity Rate (change in pp)		Employment Rate (change in pp)	
	LLM-based data	Aggregate data	LLM-based data	Aggregate data
North West	-0.3	-0.4	0.6	0.6
North East	0.3	0.2	0.8	0.7
Centre	-0.2	-0.1	1.1	1.2
South and Islands	0.4	0.4	1.8	1.8
Italy	0.1	0.1	1.2	1.2

The table reports the change between 2019 and 2023 for the indicated variables referred to the population of at least 15 years of age. The columns headed as "LLM-based data" computes these values by aggregating LLM-level data weighting each LLM by its resident population in the same age group. The columns headed as "Aggregate data" compute these values by official data at macro-area level on population by labour status in the same age group.

Table A.3: Correlation between 15-64 and 15-89 age groups from province-level data

	15-64 and 15-89 age groups	
	Correlation Coeff.	Regression R^2
Change in activity rate 2019-2023	0.95***	0.90
Change in employment rate 2019-2023	0.95***	0.91

The table reports statistics from province-level data about the relationship of the changes in employment and activity rate over the 2019-2023 interval between the 15-64 age group and the 15-89 age group (the widest age group for which data are published at the province level). The R^2 refers to a regression of the 15-64 age-group variable on a constant and the corresponding 15-89 age-group variable.

Table A.4: Summary statistics

Variable	Mean	Std. Dev.	1st quartile	2nd quartile	3rd quartile
$\Delta act.rate_{2023-2019}$	0.35	1.40	-0.53	0.34	1.27
$\Delta emp.rate_{2023-2019}$	1.57	1.32	0.65	1.48	2.46
$\Delta WFH^{15-64,T}_{2022-2019}$	3.98	7.79	0.23	1.56	4.61
$\Delta WFH^{15-64,M}_{2022-2019}$	3.68	6.75	0.13	1.31	4.35
$\Delta WFH^{15-64,F}_{2022-2019}$	4.41	9.59	0.40	1.88	5.06
Share of graduates	0.10	0.03	0.08	0.10	0.12
Log of resident population	10.70	1.13	9.95	10.70	11.40
Share of workers in firms $\geq$ 250 employed	0.05	0.06	0.00	0.02	0.08
Share of workers in firms $<$ 10 employed	0.60	0.14	0.49	0.60	0.71
Share of workers in manufacturing	0.21	0.13	0.11	0.18	0.30
Share of sectors with more female workforce	0.38	0.10	0.31	0.37	0.43
Employees' average age	41.80	1.06	41.10	41.90	42.70
Share of population $\geq$ 65 yrs out of pop. $\geq$ 15 yrs	0.29	0.04	0.26	0.28	0.31
Share of female employees	37.00	3.75	34.40	37.60	39.80
South	0.46	0.50	0	0	1
LLM class: unspecialized	0.19	0.39	0	0	0
LLM class: urban	0.15	0.36	0	0	0
LLM class: non-manufacturing non-urban	0.22	0.41	0	0	0
LLM class: "made in Italy" manufacturing	0.31	0.46	0	0	1
LLM class: heavy manufacturing	0.14	0.35	0	0	0
Export class: 1st fourth	0.25	0.43	0	0	1
Export class: 2nd fourth	0.25	0.43	0	0	0
Export class: 3rd fourth	0.25	0.43	0	0	1
Export class: 4th fourth	0.25	0.43	0	0	0

The table reports summary statistics for variables used in the empirical model. The Share of sectors with more female workforce is computed as the share of 1-digit sectors where the incidence of female workers is above its average incidence across all sectors. "Made in Italy" LLMs are those LLMs specialized in textiles, clothing, leather, machine manufacture, wood and furniture, food and beverages, jewelery, glasses, musical instruments. Heavy manufacturing includes automotive and other transports, metal, building material, chemistry, steel making and pharmaceuticals. Non-manufacturing non-urban LLMs includes LLMs tourism-oriented or agricultural-oriented. All other variables are described in Section 3.1. All variables without a time subscript are reported at the 2019 value or an average over earlier years.

Table A.5: Pre-trend regression

	Activity rate		Employment rate	
	unconditional	conditional	unconditional	conditional
	(1)	(2)	(3)	(4)
WFHP	-6.529**	0.127	-7.244**	1.500
	(1.755)	(2.670)	(1.568)	(2.362)

The table refers to OLS regression of the change in activity and employment rates between 2015 and 2019 and the instrument. The columns labeled as "unconditional" refer to regressions that do not include the set of control variables included in model 1, whereas the columns as "conditional" refer to regressions that do include it. Robust standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table A.6: Pre-trend regression. Varying time-span

	$\Delta_{2013-2019}$		$\Delta_{2014-2019}$		$\Delta_{2015-2019}$		$\Delta_{2016-2019}$		$\Delta_{2017-2019}$	
	uncond.	cond.	uncond.	cond.	uncond.	cond.	uncond.	cond.	uncond.	cond.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Activity rate									
WFHP	-10.865**	5.410+	-8.551**	4.031	-6.529**	0.127	-7.023**	-2.250	-4.790**	-3.007
	(2.295)	(3.249)	(1.865)	(2.639)	(1.755)	(2.670)	(1.584)	(2.384)	(1.584)	(2.593)
	Employment rate									
WFHP	-12.110**	4.961	-8.906**	4.554+	-7.244**	1.500	-6.587**	0.000	-4.910**	-3.112
	(2.218)	(3.198)	(1.727)	(2.494)	(1.568)	(2.362)	(1.351)	(2.028)	(1.372)	(2.258)

The table refers to OLS regression of the change in activity and employment rates between the years indicated in columns and the instrument. The columns labeled as "uncond." refer to regressions that do not include the set of control variables included in model 1, whereas the columns as "cond." refer to regressions that do include it. Robust standard errors in parentheses; $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$.

Table A.7: Monotonicity checks

	$\Delta WFH^{15-64,T}$		$\Delta WFH^{15-64,M}$		$\Delta WFH^{15-64,F}$	
	low	high	low	high	low	high
	(1)	(2)	(3)	(4)	(5)	(6)
WFH potential	73.171*	193.149**	59.271*	190.496**	90.770^{+}	196.419**
	(35.669)	(41.594)	(25.526)	(39.616)	(50.765)	(46.098)
Controls	Y	Y	Y	Y	Y	Y
Obs	302	304	302	304	302	304
R^2	0.169	0.592	0.256	0.610	0.121	0.534
	$\Delta WFH^{25-49,T}$		$\Delta WFH^{25-49,M}$		$\Delta WFH^{25-49,F}$	
	low	high	low	high	low	high
	(1)	(2)	(3)	(4)	(5)	(6)
WFH potential	59.868^{+}	114.187**	46.680*	107.317**	76.210^{+}	122.927**
	(30.676)	(27.463)	(21.111)	(24.830)	(44.255)	(32.385)
Controls	Y	Y	Y	Y	Y	Y
Obs	302	304	302	304	302	304
R^2	0.143	0.610	0.216	0.635	0.109	0.531

The table refers to OLS coefficient of the instrument in the first-stage regressions where the dependent variable is the change in actual use of WFH between 2019 and 2022 among workers of the indicated sex and age-class (T, M and F indicates respectively total, male, and female). Each regression is run separately for the subsamples of LLMs with WFHP below and above the median. All regressions include the set of control variables specified in model 1. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.8: Sector-level regressions

	First-stage	Reduced form		Two stage least square	
		Act.rate	Empl.rate	Act.rate	Empl.rate
	(1)	(2)	(3)	(4)	(5)
$WFHP_j$	78.544**	9.778*	7.640*		
	(18.093)	(4.201)	(3.385)		
$\Delta WFH^{15-64,T}_{2022-2019,j}$				0.124*	0.097*
				(0.058)	(0.044)
Observations	245	245	245	245	245
Rob. F-stat				18.85	18.85

The table reports the shift-level regression computed according to the methodology in Borusyak *et al.* (2021). Shift-level variable are obtained through the routine *ssaggregate* (Borusyak *et al.*, 2018). Observations are weighted according to the industry share at the aggregate level. Standard errors clustered by 2-digit industry are in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.9: Weighted estimates of the baseline model

	Activity rate		Employment rate	
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
β	-0.002	0.006	-0.002	-0.003
	(0.006)	(0.011)	(0.005)	(0.008)
Controls	Y	Y	Y	Y
Obs.	606	606	606	606
Rob. F-stat		21.175		21.175
R^2	0.304	0.300	0.515	0.515

The table reports weighted OLS and weighted 2SLS estimates for β in model (1) where $g = T$ and a=15-64 years. In every estimate each LLM is weighted based on its resident population in 2019. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.10: Initial conditions as placebo outcomes

	(1)	(2)	(3)
	Population density	Foreign share	Med-high productive LLM
WFH potential	2.306	-0.076	0.574
	(1.514)	(0.068)	(0.770)
Controls	Y	Y	Y
Obs.	606	606	606
R^2	0.689	0.537	0.603

The table reports reduced-form regression of model 1 considering as depdendent variable: in column (1), the log population densitiy in 2019; in column (2) the share of foreign population in 2019; in column (3) a dummy equal to 1 LLMs with medium to high labour productivity. Labour productivity in column (3) is based on LLM classes computed by Istat before the pandemic, grouping classes 3, 4, and 5 (the dummy is equal to 1 for 51% of LLMs in the estimation sample). Robust standard errors are in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.11: Alternative instruments. Reduced forms.

	Participation rate		Employment rate	
	2015-19	2019-23	2015-19	2019-23
	(1)	(2)	(3)	(4)
WFHP (alt. measurement)	-1.486	8.003*	1.799	5.720*
	(2.972)	(3.123)	(2.566)	(2.530)
Controls	Y	Y	Y	Y
Obs	606	606	606	606
R^2	0.160	0.267	0.196	0.445
Average band speed	-0.002	0.006**	-0.001	0.005**
	(0.001)	(0.001)	(0.001)	(0.001)
Controls	Y	Y	Y	Y
Obs	606	606	606	606
R^2	0.164	0.290	0.197	0.464

The table reports the reduced forms for the effect of the reported instrument on the change in the dependent variable in the period reported in columns. The alternative measure of WFHP is based on the Dingel and Neiman (2020)'s measurement at the sectoral level. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.12: Alternative instruments. Two stage least squares estimates.

	WFHP Dingel and Neiman (2020)		Average band speed	
	Activity rate	Employment rate	Activity rate	Employment rate
	(1)	(2)	(3)	(4)
β	0.119*	0.085*	0.246**	0.200**
	(0.054)	(0.042)	(0.087)	(0.071)
Controls	Y	Y	Y	Y
Obs	606	606	606	606
Rob. F-stat	15.873	15.873	9.079	9.079

The table reports the two stage least square estimates for β in model (1) using as instrument either the WFH potential at the local level based on the Dingel and Neiman (2020) measure or the average band speed in the LLM for the dependent variable indicated in columns. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.13: Robustness check: excluding ICT sector

	Reduced form				Two stage least square	
	2015-2019		2019-2023		2019-2023	
	Act.rate	Empl.rate	Act.rate	Empl.rate	Act.rate	Empl.rate
	(1)	(2)	(3)	(4)	(5)	(6)
$WFHP^{No\_ICT}$	1.468	2.438	9.978**	7.068**		
	(2.858)	(2.499)	(3.095)	(2.564)		
$\Delta WFH^{15-64,T}_{2022-2019}$					0.135*	0.095*
					(0.055)	(0.043)
Controls	Y	Y	Y	Y	Y	Y
Observations	606	606	606	606	606	606
Rob. F-stat					13.896	13.896

The table reports the results for the reduced form and the 2SLS regressions obtained when the ICT sector (industries from 58 to 63) are excluded from the computation of the work from home potential. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.14: Alternative clustering

	Activity rate		Employment rate	
	(1)	(2)	(3)	(4)
β	0.116**	0.116*	0.087**	0.087*
	(0.041)	(0.051)	(0.033)	(0.041)
Robust std errors (baseline)	Y		Y	
Std errors clustered by main industry		Y		Y
Obs.	606	606	606	606
R^2	0.089	0.089	0.342	0.342
Rob. F-stat	21.996	11.812	21.996	11.812

The table reports two stage estimates of model 1 considering as dependent variable the activity rate (columns 1 and 2) and the employment rate (columns 3 and 4). Columns (1) and (3) reports the baseline estimates with robust standard errors; columns (2) and (4) uses standard errors clustered by the main LLM's industry. $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.15: Alternative specification of the explicative variable: 2019-21 time span.

	Activity rate		Employment rate	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
β	0.016^{**}	0.107^{**}	0.015^{**}	0.080^{*}
	(0.006)	(0.039)	(0.005)	(0.031)
Controls	Y	Y	Y	Y
Obs	606	606	606	606
Rob. F-stat		20.087		20.087
R^2	0.266	0.052	0.447	0.323

The table reports OLS and 2SLS estimates for β where the variable of interest is $\Delta WFH^{a,g}_{2021-2019,i}$, with $a = 15-64$ years old and $g = T$, i.e. both genders. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.16: Outliers exclusion. Two stage least square estimates

	Activity rate			Employment rate		
	(1)	(2)	(3)	(4)	(5)	(6)
β	0.116^{**}	0.094^{**}	0.158^{*}	0.087^{**}	0.054^{*}	0.085^{+}
	(0.041)	(0.036)	(0.064)	(0.033)	(0.027)	(0.047)
Controls	Y	Y	Y	Y	Y	Y
No outlier y		Y	Y		Y	Y
No outlier x			Y			Y
Obs	606	594	586	606	593	585
Rob. F-stat.	21.996	20.289	17.853	21.996	21.024	18.607
R^2	0.089	0.119	0.120	0.342	0.422	0.409

The table reports 2SLS estimates for β in model (1). Columns 1 and 4 refer to the whole estimation sample; columns 2 and 5 exclude outliers in the dependent variable; columns 3 and 6 excludes outliers in the dependent variable and in the explicative variable of interest ($\Delta WFH^{15-64,T}_{2022-2019,i}$). Outliers are defined as values below the 1st percentile or above the 99th percentile. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.17: Exclusion of LLMs with higher sampling errors.

	Activity rate		Employment rate	
	(OLS)	(2SLS)	(OLS)	(2SLS)
	(1)	(2)	(3)	(4)
β	0.023^{**}	0.115^{**}	0.020^{**}	0.084^{**}
	(0.004)	(0.038)	(0.004)	(0.030)
Controls	Y	Y	Y	Y
Obs	549	549	549	549
Rob. F-stat.		22.4		22.4
R^2	0.336	0.137	0.490	0.384

The table reports the OLS and 2SLS estimates for β in model (1) after excluding from the estimation sample the LLMs in the highest ten per cent of the sampling error distribution. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$

Table A.18: Heterogenity by LLM specialization

	Activity rate		Employment rate	
	Non-manufacturing	Manufacturing	Non-manufacturing	Manufacturing
	(1)	(2)	(3)	(4)
15-64 years				
β	0.104*	0.156*	0.084*	0.109*
	(0.050)	(0.061)	(0.042)	(0.048)
Obs	332	274	332	274
Rob. F-stat	10.028	18.829	10.028	18.829
Std.dev.-impact	0.962	0.854	0.775	0.593
25-49 years				
β	0.172*	0.235*	0.138^{+}	0.163*
	(0.085)	(0.092)	(0.071)	(0.072)
Obs	332	274	332	274
Rob. F-stat	8.299	18.785	8.299	18.785
Std.dev.-impact	1.163	0.861	0.936	0.597

The table reports 2SLS estimates for β in model (1) where $g = T$ and a=15-64 years (top panel) and 25-49 years (bottom panel), distinguishing between LLMs specialized in manufacturing industries and LLMs specialized in other sectors or not specialized. The 2SLS uses WFH potential as instrument. Robust standard errors in parentheses; $^{+}$ $p < .10$, * $p < .05$, ** $p < .01$