I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16906

Did COVID-19 (Permanently) Raise the Demand for "Teleworkable" Jobs?

M. Bratti
I. Brunetti
A. Corvasce
A. Maida
A. Ricci

APRIL 2024

DISCUSSION PAPER SERIES

IZA DP No. 16906

Did COVID-19 (Permanently) Raise the Demand for "Teleworkable" Jobs?

Massimiliano Bratti
Università degli Studi di Milano, IZA and GLO

I. Brunetti
Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP) and GLO

A. Corvasce
Università degli Studi di Milano

A. Maida
Università degli Studi di Milano

A. Ricci
Istituto Nazionale per l'Analisi delle Politiche Pubbliche (INAPP)

APRIL 2024

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Did COVID-19 (Permanently) Raise the Demand for "Teleworkable" Jobs?*

This study leverages detailed administrative data on firms' job flows and variation across Local Labor Markets (LLMs) in the spread of COVID-19 to investigate shifts in labor demand prompted by the pandemic. To this end, we exploit the large spatial variation in the intensity of the pandemic observed in Italy. Namely, we investigate the effect of COVID-19 intensity on the composition of new hires in terms of jobs suitable for "working from home" (WFH), which emerged as a new standard during the pandemic. Our results reveal a significant increase in teleworkable-job hires in LLMs that were more severely hit by the pandemic, primarily driven by permanent contracts. An event study analysis uncovers substantial heterogeneity over time. Indeed, the effect was short-term and lasted only for two semesters after the pandemic's outbreak. Although this shift was transitory, by involving permanent hires, it had persistent effects on the structure of the workforce. An effect-heterogeneity analysis shows that effects were greater on the demand for female and younger workers and hires of larger firms, of service firms, and of those located in Northern Italy.

JEL Classification: D22, J23, J24

Keywords: working from home, telework, labor demand, COVID-19, Italy

Corresponding author:
Massimiliano Bratti
Department of Economics, Management and Quantitative Methods (DEMM)
University of Milan
via Conservatorio 7
20123 Milan
Italy
E-mail: massimiliano.bratti@unimi.it

* This paper was produced by Irene Brunetti and Andrea Ricci as part of the Inapp PTA 2021-2023, with reference to the lines of activity pertaining to the "Struttura Imprese e Lavoro." The views expressed in this paper are those of the authors and do not necessarily reflect those of INAPP. Massimiliano Bratti, Alessandro Corvasce e Agata Maida gratefully acknowledge funding from the project "Grandi Sfide di Ateneo" of the University of Milan. The usual disclaimers apply.

1 Introduction

The COVID-19 pandemic, with its ensuing lockdowns, wrought profound shifts in both people's lives and firms' operations. As mobility restrictions compelled firms to reimagine their work structures, the adoption of remote work (working from home, WFH hereafter) became widespread (Barrero et al. 2023; Bick et al. 2023; Bartik et al. 2020).

While exant research extensively explores the impact of WFH on productivity (Angelici and Profeta 2023; Morikawa 2022; Bartik et al. 2020; Etheridge et al. 2020; Feng and Savani 2020), analyzes the actual use of WFH (Aksoy et al. 2023), the "teleworkability" of the current workforce (Dingel and Neiman 2020; Basso et al. 2020) or the characteristics of workers working from home (Alipour et al. 2023; Bonacini et al. 2021), our study takes a different stance. Although some studies have examined the *potential* re-allocative impact of COVID-19 in the labor market (Bonacini et al. 2021; Basso et al. 2020), predicting large changes, to the best of our knowledge, evidence on the *actual* reallocative effects of the pandemic toward teleworkable jobs is still lacking. We aim to fill this gap, and we study whether COVID-19 induced a lasting transformation in the occupational fabric of the economy. Specifically, we inquire if the pandemic prompted an upsurge in jobs conducive to remote work (i.e., "teleworkable" jobs) and whether this shift was transient or enduring. Although our study provides direct evidence on COVID-19, it informs more in general on firms' capacity to adapt their labor demand in the face of a large and unexpected health shock.

Italy provides the ideal setting to assess the impact of COVID-19 on the labor market. First, Italy was among the first countries to be hit by COVID-19, which left no room to firms for adjusting their workforce's characteristics before the pandemic outbreak. This minimizes the risk of "anticipation effects."[1] Second, Italy was characterized by a large spatial heterogeneity in the COVID-19 spread (Gibertoni et al. 2021), even across neighboring regions (Berta et al. 2021). Our study relies on geographical variation in the diffusion of COVID-19, gauged through excess mortality measures (Msemburi et al. 2023) at the Local Labor Market (LLM) level,[2] to identify the causal effect of COVID-19 on firms' labor demand.[3] Cross-sectional variation was huge, with excess mortality rates as low as 3.5% in the first 25th percentile and as high as 45.3% in the 95th percentile.

We employ high-quality data from Italy. Information on job creation comes from an employer-employee administrative dataset provided by the Italian Ministry of Labor and

[1] These effects are investigated through an event-study analysis.

[2] In Italian, *Sistemi Locali del Lavoro* (SLL).

[3] Strictly speaking, by looking at employment, we study a labor market equilibrium outcome, i.e. we only observe new positions (vacancies) that are filled.

Social Policies that tracks all events related to a job position (hiring, contractual transformation —- e.g. from a fixed-term to an open-ended arrangement —-, firing, resignation). To classify occupations according to their potential WFH, we utilize the *Indagine Campionaria delle Professioni* (ICP), akin to the U.S. O*NET, conducted by the INAPP (*Istituto Nazionale per l'Analisi delle Politiche Pubbliche*). The ICP survey, last administered in 2013, gathers detailed information on all the 5-digit occupations existing in the Italian labor market (i.e., for a total of 813 occupational codes).

Notably, we pioneer the application of a "teleworkability" job measure to scrutinize post-pandemic firms' hiring patterns using administrative data, shedding light on potentially enduring shifts in labor demand triggered by COVID-19. Our study endeavors to address pivotal questions: (1) Did the pandemic prompt a short-term surge in firms seeking teleworkable jobs compared to non-teleworkable jobs? (2) Does this trend endure in the medium run? Section 3 elucidates a detailed definition of teleworkable jobs based on ICP.

Several reasons make studying the labor demand effects of the pandemic on teleworkable jobs important. Understanding how the pandemic influenced the demand for teleworkable jobs throws light on the adaptability of work structures in response to health crises. This knowledge can guide future workforce planning strategies. Examining the demand for teleworkable jobs post-COVID-19 allows insights into potential shifts in required skills and qualifications. This information is crucial for educational institutions and policymakers to align training programs with evolving job requirements. Past studies suggest that the pandemic induced a persistent reallocation in the labor market (Barrero et al. 2023). Teleworkable jobs are often considered "good jobs," offering higher pay, requiring advanced qualifications, and providing increased work autonomy. Analyzing the demand for teleworkable jobs contributes to understanding the broader labor market dynamics after COVID-19, aiding in informed policymaking.

Our analysis emphasizes that the severity of COVID-19 impacted firms' teleworkable job creation, primarily with permanent contracts. The share of WFH jobs created with open-ended contracts after COVID-19 rose on average by 0.2 percentage points (1% measured at the pre-pandemic baseline) for a one-SD increase in excess mortality at the LLM level. When we allow for the effects to be year-specific, using an event-study analysis, we document that the average post-COVID effect hides in reality substantial heterogeneity over time. Indeed, although the effect was short-term and lasted only for two semesters after the pandemic's outbreak, in these semesters the increase amounted to up to 4% on open-ended contracts. The event-study analysis also confirms that the observed effects are not attributable to an ongoing trend that started before the pandemic. This attenuates concerns that LLMs that were more heavily hit by the pandemic — typically LLMs in Northern Italy — were also those experiencing higher WFH job creation before the health emergency and lends support to the parallel trend assumption.

Our results are robust to a battery of robustness checks, including using a continuous measure of WFH job creation, changes in the sample trimming criteria used in the analysis, and the inclusion of broad occupational indicators to check whether the effects are driven by certain occupations. A heterogeneity analysis underscores that effects were higher: on female and younger workers; on workers in Northern and partly in Southern Italy compared to the Center of the country; in the service sector; and for larger firms. Finally, a before-after analysis, which compares the dynamics in WFH job creation before vs. after the pandemic without necessarily relating it to the local intensity of COVID-19's spread, gives qualitatively consistent results, albeit larger estimates.

The remainder of the paper is structured as follows. In Section 2, we report a short review of some related literature. In Section 3, we describe the data. Section 4 presents the empirical strategy. Section 5 includes the main estimation results, some robustness tests, and an effect-heterogeneity analysis. The results of a before-after analysis are reported in Section 6. Section 7 draws conclusions.

2 Related literature

The outbreak of the Coronavirus pandemic in 2020 had an unprecedented impact on the global labor market. For instance, the widespread adoption of working from home across a vast range of industries and sectors has been described as the largest change to the U.S. economy since World War II (Bloom 2023). As a result of this abrupt change, there has been a surge in the literature examining the economic consequences of COVID-19. Without the pretension of being exhaustive, this section aims to provide an overview of the key findings and insights from recent research on the determinants and diffusion of WFH, as well as its implications and effects on the labor market.[4]

Some studies focus on estimating the share and types of work that can be carried out from home or remotely and their diffusion. Dingel and Neiman (2020) provides the first estimates for the U.S., while Basso et al. (2020) and Barbieri et al. (2022) present similar analyses for Italy. These papers use nationally representative survey data on occupational characteristics to identify suitable occupations for remote work. Dingel and Neiman (2020) uses the rich information on worker activities and occupational characteristics in the O*NET database to build an index of propensity to work from home. Results suggest

[4] Interested readers can refer to Lee (2023) for a recent literature review.

that nearly 37% of jobs in the U.S. can be performed entirely from home. The authors also note significant variations across cities and industries, as well as the fact that remote jobs tend to be more highly paid than non-remote jobs. Barbieri et al. (2022) uses highly detailed information on the attributes of fine-grained occupations collected from ICP — also used in this paper — and estimates that the share of Italian employees that could potentially work remotely is around 33% in the total Italian economy. Buia et al. (2023) analyzes the European SHARE survey and focuses on individuals who worked continuously since the start of the pandemic; the authors found that around 22% of men and 30% of women were working remotely between 2020 and 2021. However, Crescenzi et al. (2022) argues that relying solely on survey data to estimate the potential for remote work may overestimate the share of jobs that are carried out remotely. The paper examines the actual number of jobs performed at home during the pandemic using unique administrative data on the universe of Italian workers from the National Institute for Insurance against Accidents at Work (INAIL). Results suggest that only 12% of the workforce was able to work remotely.

Another area in which the literature has focused is how the spread of WFH triggered labor market adjustments. As claimed by various scholars, WFH is not a temporary phenomenon but will lead to structural changes. Basso et al. (2020), building on the WFH indicator described earlier, analyzes the need for worker relocation and for major restructuring for firms that offered non-WFH jobs. The need to respond to a decrease in demand for goods and services that pose a higher epidemiological risk, coupled with the necessity of restructuring the workforce more flexibly, could cause a structural transformation, with a permanent shrinkage of certain occupations and a growth in labor demand in other jobs or sectors. According to Basso et al. (2020), it is very likely that training in digital skills will be required to ease this reallocation. Digitalization will be widespread beyond occupations where WFH is already in place; it will also be important among those that are unsafe under current technologies, as there will be a need to have less physical proximity to avoid contagion risks and improve competitiveness. Barrero et al. (2021) estimates the short-term impact of the pandemic on workers' reallocation and conclude that this shock caused three new hires for every ten layoffs. The authors predict that much of this impact will persist, with 42% of recent layoffs becoming permanent job losses. Barrero et al. (2021) also determined that almost 22% of full workdays will be supplied from home after the pandemic ends, which is about four times the pre-pandemic WFH share. This increase is estimated to be beneficial for both workers (as it saves commuting time and reduces spending) and firms (as they benefit from increased productivity and re-optimized working arrangements).

One of the significant concerns for employers when considering the implementation of WFH arrangements is indeed productivity. Bloom et al. (2015) and Angelici and Profeta (2023) conducted pioneering randomized control trials to evaluate the impact of WFH. Bloom et al. (2015) reports evidence from a field experiment with employees from a Chinese travel agency finding that WFH led to a 13% increase in productivity, which they attributed to a quieter working environment and reduced time spent on commuting. Angelici and Profeta (2023) finds causal evidence that flexibility in time and place of work ("smart working") increases the objective productivity of workers and improves their well-being and work-life balance. Bartik et al. (2020) surveys large and small U.S. firms to analyze the prevalence and productivity of remote work. The authors find large heterogeneity across industries, as WFH is much more common in industries with better-educated and better-paid workers, thus highlighting the challenge of moving many industries to this new practice. Again, their results pinpoint that there was less productivity loss from remote working in better-educated and higher-paid industries. Aksoy et al. (2023) fields a unique global survey that yields individual-level data on demographics, WFH levels, employer plans, and worker desires and perceptions related to WFH, to depict the effect of the pandemic on WFH adoption and dynamics. The study identifies a positive effect on productivity that supports the diffusion of WFH and its widespread adoption even after emergency times. Moreover, this is particularly true for women and more educated workers. Other studies report instead negative impacts on productivity. A study by DeFilippis et al. (2020) analyzes the effects of WFH during the COVID-19 pandemic in 16 large metropolitan areas in North America, Europe, and the Middle East. The authors document that the average workday length increased by 48.5 minutes, but this increase in working hours did not necessarily translate into higher worker productivity. A study for Japan (Morikawa 2022) reveals that the mean productivity of WFH relative to working at the usual workplace was about 60%–70%. Productivity was lower for firms and employees who had only recently started working from home due to the COVID-19 pandemic. Focusing on the UK Labor market Bloom et al. (2023) documents that total factor productivity (TFP) fell by up to 5% during 2020-21 in the UK, but hourly labor productivity was positively affected. The authors report significant heterogeneity across firms and sectors, with the largest negative impacts on sectors needing extensive in-person activity. These results resemble those of Etheridge et al. (2020), which documents that in the UK workers at home reported being approximately as productive as before the pandemic, on average. However, productivity varied substantially across socioeconomic groups, industries, and occupations.

Changes in the way firms organize work and WFH adoption are likely to have uneven effects on workers. A study in Italy shows how a permanent surge in WFH may exacerbates income inequality. Bonacini et al. (2021) documents that a permanent adoption of WFH raises average labor incomes, but benefits mainly high-educated and high-paid employees, and employees in provinces more heavily affected by COVID-19. Similar evidence exists for other countries. A study for the U.S. (Mongey et al. 2021) reports that workers in low-WFH jobs were more economically vulnerable: they had lower education, lower income, fewer liquid assets, and were more likely to be renters. Alipour et al. (2023) show that WFH jobs in Germany are concentrated in the digitalized industries and involve cognitive tasks. So WFH, like other important changes in the labor market, is likely to be skill-biased and increase polarization.

In conclusion, the effects of WFH on the labor market are multifaceted and depend on various factors such as job type, industry, and individual circumstances. While most research generally indicates positive effects on productivity — with some exceptions —, worker satisfaction, and labor market participation, concerns remain regarding potential impacts on income inequality. Further research is needed to understand the long-term implications of WFH policies and how they can be optimized to promote better and innovative working arrangements that could benefit both workers and firms.

3 Data

This study utilizes a unique dataset obtained by linking an administrative data source on job flows to a survey on occupations' characteristics to provide insights into potential changes in labor demand triggered by the Coronavirus pandemic. The first source is the archive of the *Compulsory Communications System* ("Sistema delle Comunicazioni Obbligatorie", COB hereafter) administered by the Ministry of Labor and Social Policies, which records from 2009 information on each working relationship that started, changed or ended for firing, dismissal, retirement, or transformation (e.g., from a fixed-term to an open-ended contract) for all individuals working in Italy as employees. It gathers detailed information on age, gender, the type of contract (part-time or full-time, temporary or permanent), occupation (5-digit), educational attainment, the sector of activity, and the geographical localization (the LLM) of the work arrangement. From this archive, we use a representative sample obtained by drawing data from four birth dates for each month, for a total of 48 birth dates per year. Using the detailed information provided by COB, we can examine labor market dynamics comprehensively, and analyze the creation of teleworkable jobs across different dimensions of employer-employee relationships.

To classify occupations according to their potential for remote work, we use the *Indagine*

Campionaria delle Professioni (ICP) conducted by INAPP. The ICP survey was last run in 2013 and involves 16,000 workers recording detailed information on all the 5-digit occupations (i.e., 813 occupational codes) in the Italian labor market. The ICP is the Italian equivalent of the U.S. O*NET, and a relevant aspect of it is that job task variables are specific to the national labor market, accounting for the structure of the industrial relations characterizing the Italian economy. Therefore, the use of ICP avoids potential methodological problems that may arise when information related to the U.S. occupational structure (i.e., contained in the U.S. O*Net repertoire) is matched with labor market data referring to European countries.

Following Dingel and Neiman (2020) and Barbieri et al. (2022), we compute the teleworkability of each profession at the 3-digit level by averaging the responses to seven specific questions: (i) importance of physical activities (reversely); (ii) importance of working with computers; (iii) importance of maneuvering vehicles or equipment (reversely); (iv) requirement of face-to-face interactions (reversely); (v) dealing with external customers (reversely); (vi) physical proximity (reversely); (vii) time spent standing (reversely). Each profession j is given a score (ICP index$_j$).

The analysis focuses on the period around the pandemic, from the first quarter of 2017 to the four quarter of 2021. As for sample selection, we consider all contractual arrangements, with the exception of the armed forces, involving employees aged between 17 and 64, and, since our main focus is to analyze relevant shifts in labor demand, we remove all contracts with a duration below 30 days (10th percentile). Indeed, they are not so informative regarding substantial transformations of the workforce. After imposing these criteria, our sample comprises 5,998,993 observations over the period 2017-2021. Adopting this time span enables us to carry out the analysis on a symmetric window around the pandemic outbreak.

3.1 Excess mortality

To assess the differential impact of the COVID-19 pandemic across different areas of Italy, this study employs mortality data from the Italian National Institute of Statistics (ISTAT).[5] Excess deaths/mortality were considered a crucial measure to monitor the pandemic's impact, both nationally and locally (Buonanno et al. 2020; Msemburi et al. 2023). The mortality data provide the count of daily deaths for each municipality in Italy by the municipality of residence. By comparing the average mortality during the March-May period in the years 2015-2019 with the mortality in the same quarter in 2020, we calculate

[5] https://www.istat.it/it/archivio/240401.

an excess *mortality rate* at the LLM level. LLMs are sub-regional geographical areas, comparable to the U.S. commuting zones, where the bulk of the labor force lives and works, and where establishments can find the main part of the labor force necessary to fill their vacancies. Excess mortality measured at the LLM level captures the differential firms' exposure to the pandemic shock depending on the LLM in which they were located.

Specifically, the excess mortality ratio is computed as:

$$Exc_l = \frac{M_{l,2020} - \overline{M}_{l,2015-2019}}{\overline{M}_{l,2015-2019}} * 100 \tag{1}$$

where $M_{l,2020}$ is the number of deaths over the March-May 2020 period and $\overline{M}_{i,2015-2020}$ represents the average number of annual deaths in the period 2015-2029, in each l Local Labor Market.[6] For ease of interpretation, we normalize the variable to have zero mean and unit standard deviation, so that the coefficients can be interpreted as the increase in job creation determined by a one-SD increase in excess mortality.

Figure 1 details the distribution across the Italian LLMs of the excess mortality, with darker shades of red representing higher levels of mortality. In line with the literature, it can be noticed that there was a strong geographical pattern, with the highest level of estimated excess mortality occurring in just two northern regions (Lombardy and Piedmont) and other Northern regions such as Veneto, Trentino Alto Adige, Friuli Venezia Giulia, and Emilia Romagna exhibiting more pronounced variability across LLMs. Central Italy and the Southern and Insular LLMs also display noteworthy differences in excess mortality. This geographic heterogeneity provides an ideal setting for the investigation of the labor market effects of the pandemic. Differences are partly linked to the implementation of specific policies by regional administrations such as lockdowns, mobility restrictions, and COVID-19 testing, which often generated noticeable differences even between municipalities belonging to the same region (Gibertoni et al. 2021), but also to exogenous factors related to specific events, such as, for instance, football matches (Alfano 2022).

3.2 Firms' WFH (i.e. teleworkable) jobs creation measure

In order to evaluate the response of the Italian labor market to the spreading of COVID-19 and to detect whether there has been a shift in demand toward occupations more prone to WFH, we first build an indicator that measures the share of WFH occupations within

[6] This is the so-called P-score method. In particular, imagine that the average number of deaths between 2015 and 2019 is 100, which is also the one that would be expected for 2020 in the absence of COVID-19, while the actual number of deaths in 2020 is 140, the P-score is 40%. As stressed by Msemburi et al. (2023) the P-score implicitly considers both the population size and the age structure.

each firm and according to the type of contract (open-ended, fixed-term, other residuals types of contracts). The inclusion of the type of contract in the analysis produces a major advantage. First, since at the time of the COVID-19 outbreak firms were uncertain about how long the pandemic was going to last, we might expect a differential effect on temporary and permanent jobs, which can be investigated using interaction terms with the contract type. Second, it allows us to include contract fixed effects (FE) in our estimation and hence to control for intrinsic differences between permanent and temporary hires. Following the approach proposed by Autor and Dorn (2013), the share of highly-teleworkable job creation is defined as follows:

$$\text{WFH Share}_{itc} = \left[\sum_j N_{ijct} * 1[\text{ICP Index}_j > ICP^{66pct}] \right] / N_{it} \tag{2}$$

where N_{ijct} is the number of hires made by firm i, for occupation j, at time t, with the type of contract c; the ICP Index$_j$ is the index built from the ICP survey that measures how much occupation j is prone to WFH, and $1[.]$ is an indicator function equal to one for hires in an occupation with an ICP index's value in the top 33% of the ICP distribution, and 0 otherwise. N_{it} is the total number of hires made by firm i in time t. Figure 2 depicts the difference in the WFH share before and after the pandemic aggregated at the LLM level; darker areas represent a steeper increase.

The firm-level data provided by COB include information about firm location at the municipality level, which was used to attribute an LLM to each firm and match data on job flows with LLMs' excess mortality.[7]

3.3 Descriptive Statistics

Table 1 reports the composition of our sample according to different characteristics: the type of contracts (permanent, temporary, and other) created, the macro geographical area of the job (North, Center, and South and Islands), gender, and age class of the hired employee. The top panel suggests that the highest share of hires (68.8%) are temporary contracts, while permanent contracts are only 20%. The residual percentage is represented by hires with other typologies of contracts (i.e. apprenticeship, on-call, agency, para-subordinate contracts). The second panel shows that almost half of contracts have been created in Northern Italy (47.3%). The last two panels depict worker characteristics: the job creation slightly favors male workers (54.2%). Workers older than 55 constitute a low share of the total (10.8%) while there is a balanced distribution between the two

[7] The composition of LLMs in terms of municipalities is provided by ISTAT.

remaining age classes of under-35 (46%) and 35-54 years old workers (43.1%).

Table 2 presents a detailed breakdown of our dependent variable, the WFH hiring shares, including the mean, standard deviation, and the 25th, 75th, and 99th percentiles for the total sample and segmented by contract types and worker demographics. It reveals that, on average, 19% of new hires occur in occupations that are very suitable for WFH. Distinct variations in the share of hires in WFH jobs are noted across employment categories. Specifically, permanent and other forms of contracts show a higher average WFH share (nearly 30%) compared to temporary jobs underscoring the role of job stability in those occupations that have the advantage that they can be carried out from home. The data also highlight a gender gap in WFH hirings, with females having a notably higher average share, almost twice that of males, suggesting potential labor market segmentation or disparate access to WFH opportunities. Age-wise, there is a slight variation in WFH shares, with the under-35 and the 35-55 groups exhibiting a marginally higher average (around 15%), than the over-55 group standing at 11%. Furthermore, regional differences are pronounced, with the Northern and Central regions showing higher shares of WFH job creation (about 20%) compared to the Southern region's 13%. Finally, the last row of Table 2 highlights that excess mortality is characterized by a huge geographical variability: the 75th percentile, for instance, is three times as large as the 25th percentile, corresponding to excess mortality of 3.5% and 16%, respectively.

4 Empirical Strategy

To analyze whether the pandemic of COVID-19 caused an increase in jobs that could be done from home, we estimate the following model:

$$\text{WFH Share}_{itc} = \alpha + \beta(Exc_l * post_t) + D_i + D_c + D_l + D_t + D_y * D_t + \epsilon_{itc} \tag{3}$$

where WFH Share$_{itc}$, our main dependent variable, measures the share of WFH hires, i, c, and l represent firm, contract, and LLM subscripts respectively. Period t is defined as a combination of semester and year (y); Exc_l is the firm's LLM l's excess mortality due to COVID-19 in the March-May quarter of 2020 (compared to the average of the same quarter in 2015-2019), and is interacted with $post_t$, an indicator that identifies the post-COVID-19 periods (i.e. $y > 2019$), as in a standard Difference-in-Differences (DID) framework; this indicator allows us to identify the variable shocks that hit LLMs due to differential pandemic intensity. The coefficient of interest is β, which captures our treatment effect of interest; the estimated coefficient pins down firms' labor market responses to the severity of the pandemic in terms of WFH job creation.

For ease of interpretation, in our analysis, we normalize the excess mortality rate in standard deviations (SD), so we can state that a one-SD increase in excess mortality produces a β increase in the share of teleworkable-job hires. Thus, $\beta * 100$ provides an increase in percentage points. D_i are firm, D_c contract type, D_l LLM, D_t period (semester-time dyad), and D_y*D_t sector-by-time FEs.[8] α and ϵ are the canonical regression's constant and error term.

To inspect the parallel trend assumption, the key assumption for identification in our analysis, we have also estimated an event-study specification:

$$\text{WFH Share}_{itc} = \alpha + \sum_t \beta_t (Exc_l * D_t) + D_i + D_c + D_l + D_t + D_y * D_t + \epsilon_{itc} \tag{4}$$

in which the effect of excess mortality is allowed to vary by period (by interacting it with the period indicator D_t). The reference period for the event-study analysis is the second semester of 2019, i.e. the period just before the outbreak of the pandemic, which serves as a baseline.[9]

By comparing the post- with the pre-pandemic periods, our study investigates the changes in the WFH composition of hires associated with the differential local intensity of the pandemic.

5 Results

5.1 Main results

The DID-like estimates of Eq. (3) presented in Table 3[10] show that there was a significant increase in WFH hires in the labor market related to the intensity of the pandemic. A one-SD larger excess mortality in the LLM produced a bit less than a 0.1 percentage point (pp, hereafter) increase in WFH job creation with any contract type, as reported in

[8] LLM fixed effects are generally absorbed by firm FEs, except for firms having multiple branches spanning different LLMs.

[9] We trimmed the sample. Specifically, observations with a total number of hires (N_{it}) exceeding 8 are excluded from the estimation. This criterion removes observations that fall in the 95th percentile of the sample, which may have a disproportionate impact on the results. In what follows, a sensitivity analysis is carried out to check the robustness of our results to different sample trimming criteria.

[10] Properly speaking, it is not a DiD since there is no control group. All firms are affected by excess mortality, albeit with different intensities. So the design is more like a "Fuzzy DiD" (De Chaisemartin and d'Haultfoeuille 2018).

the first column. The increase is largely due to permanent contracts, with a rise of 0.2 pp in teleworkable jobs induced by a one-SD larger excess mortality, while the remaining contract types did not register any statistically significant increase. In percentage terms, when dividing the estimated coefficients by the pre-COVID-19 mean share of teleworkable jobs, which stands at 18.2%, the effects on total contracts and open-ended contracts amount to a 0.5% and 1% increase, respectively.

Important for our identification strategy is that the excess mortality is not simply capturing differential pre-trends in WFH job creation across LLMs. This may happen, for instance, if teleworkable job creation was already more diffused in Northern Italy before the pandemic, and northern Italy's LLMs were also the ones more intensively affected by COVID-19. Although the latter is true on average — at least for the Northern Italian regions of Lombardy and Piedmont — we have already discussed the important heterogeneity across municipalities observed even within the same macro-area (North, Center, South, and Islands). To carry out a more formal test, we estimated an event-study DiD model, in which excess mortality is interacted with all period dummies (Eq. (4)). In case of no differential pre-trends, the interactions before the pandemic outbreak should not be statistically different from zero. Figure 3-Figure 5 show the event-study estimates for different types of contracts: all, permanent, and fixed-term,[11] respectively.[12] The absence of a differential pre-trend in the estimated coefficients indicates that there were no systematic differences in the WFH composition of hires before the pandemic between LLMs that were highly vs. lowly affected by COVID-19. This finding strengthens the credibility of our research design, suggesting that any observed change in WFH patterns can be ascribed to the intensity of the pandemic rather than to pre-existing trends.

The first semester of 2020, marked as the 7th period, saw the outbreak of the Coronavirus, leading to a significant and positive shift in the proportion of WFH hires, as evidenced by the event study. This shift was particularly pronounced in the first two semesters following the onset of COVID-19, with observed increases in WFH hires across all contract types of 0.3 pp and 0.2 pp, respectively. The event study's coefficients reveal a diverse range of dynamics in these effects, indicating considerable variability. When specifically examining permanent contracts, the data show even more substantial increases in the post-COVID periods: 0.7 pp and 0.4 pp in the first and second semesters, respectively. These figures significantly surpass the average post-COVID effect of 0.2 pp obtained from the baseline analyses, translating into notable increases reaching up to 4%.

[11] In the paper, we use fixed-term and temporary contracts interchangeably.

[12] In the Appendix, we also show in Figure A.1 the dynamics pooling permanent and temporary jobs and excluding the residual contractual category.

Such findings underscore the proactive measures firms took in response to the pandemic's challenges, notably by adjusting their workforce composition to favor positions amenable to remote work. This strategic shift toward more WFH occupations likely stemmed from the immediate need to adapt work practices and environments to meet the pandemic's demands, including adhering to social distancing guidelines and overcoming lockdown restrictions. It reflects a broader trend of organizational flexibility and the prioritization of employee safety and operational continuity in the face of unprecedented organizational challenges.

Yet, the effect of the pandemic-induced shift toward WFH hires appears to be only transitory. According to the estimation results, this shift lasted for two semesters. On the one hand, this indicates that firms' response to the pandemic in terms of increasing WFH capacity was a temporary measure, potentially reflecting the evolving nature of the crisis and the dynamic nature of work arrangements during this period. On the other hand, the prevalent permanent nature of the contracts involving WFH workers in the two affected periods suggests that even short-time decisions might have a long-lasting effect on the composition of the workforce.

5.2 Effect-heterogeneity analysis

5.2.1 Worker characteristics

To harness the detailed information within the COB dataset and disentangle various dynamics across workers, we conducted several heterogeneity analyses based on different worker characteristics. To this aim, we estimated Eq. (3) with a slightly modified dependent variable: WFH Share$_{iltcg}$, where the subscript g represents worker gender or age, alternatively. Consequently, we constructed our dependent variable with a more refined level of aggregation. Descriptive statistics for these variables are provided in Table 2.

In Figure A.2 and Figure A.3 in Appendix A, we present event-study estimates by gender. We observe a positive and statistically significant increase for male workers, persisting for two semesters following the pandemic outbreak and amounting to 0.3 and 0.2 pp but then significantly decreasing. When examining the results for female workers, we find a similar increase in magnitude and persistence; however, the parallel trend assumption is violated. It is possible that the national law on "*lavoro agile*" (i.e. "agile work", another definition of "telework" used in Italy),[13] had a distinct impact on female workers, given their propensity to benefit from WFH (Angelici and Profeta 2023; Aksoy et al. 2023). We re-estimated the model for women in different age bins to shed light on the

[13] *"Legge nazionale sul lavoro agile," art. 18 Legge 22 maggio 2017, n. 81.*

possible causes of the observed pre-trends. Results, reported in Figure A.4 -Figure A.6, highlight that the presence of significant differences before the COVID-19 outbreaks in the dynamics of WFH hires is mainly due to young women, those who also show the strongest increase: around 0.4 pp. In light of the extant literature (Couch et al. 2022, e.g.,), this result can be ascribed to a greater desire for work-home balance originated by those women who are in the age of having young children This is true even before the pandemic and could have led to a greater influx of female workers toward professions more prone to WFH.

In Figure A.7 in Appendix A, we analyze young workers under 35, where the increase of 0.2 pp is significant and lasts for almost three periods. This aligns well with evidence indicating that younger workers are more inclined to WFH and possess better skills to adopt the IT tools necessary for effectively doing it. Figure A.8 presents the results for workers aged 35–55. Similarly, we observe an increase of 0.2 pp that appears to be shorter term, lasting for two periods only and then becoming negative but non-significant. Finally, Figure A.9 reports the results for workers aged over 55 years, indicating almost no effect. Thus, expectedly, older workers seem to be less affected by the transition to WFH. Moreover, we do not observe any violation of the parallel trend assumption for any age class.

5.2.2 Firm characteristics

Shifting now our attention to firm characteristics, we considered effect heterogeneity by the different geographic macro-regions where firms were located. Figure A.10 in Appendix A depicts the results for the North, and we can observe a significant increase of 0.3 pp, that lasts for at least 2 semesters after the pandemic; these results are in line with the hypothesis that WFH professions are more demanded and common in the North, where there is the greater number of technological and innovative firms. In Figure A.11, on the other hand, we can notice how in the Center there is just a small change, which is however not significant. In Figure A.12, we can observe in the South a significant increase of 0.7 pp only during the second semester of 2020. These results suggest that in the South there has been a catching-up dynamic after the pandemic, with a greater influx of new workers in those professions that can better fit the new working arrangements.

Then, we classified companies by their predominant economic activity. We have followed the ISTAT definitions based on 2-digit ATECO code[14] and made a distinction be-

[14] ATECO is the classification of economic activities adopted by ISTAT and is the Italian translation of the NACE European classification.

tween manufacturing and service-oriented activities.[15] Figure A.13 and Figure A.14 in Appendix A report the results of this analysis; it is clear that the increase in the share of WFH professions is mainly due to service firms, which show an increase of around 0.2 pp. Manufacturing firms, on the contrary, show no significant increase; however it should be noticed that there has been a positive shift in the trend after the pandemic outbreak also for those firms. These results are in line with the hypothesis that WFH is more easily implemented among service workers, who are less required to interact with machinery, tools, and materials physically.

Moreover, we also took into account heterogeneity by firm size based on the number of employees. We have categorized firms into three classes: small (less than 50 employees), medium (between 50 and 250 employees), and large (over 250 employees). In order to get information on the number of employees we had to match our COB dataset to ASIA, the Italian statistical register of active businesses, but this came at a cost. The caveat is that, due to data availability, we have been able to get the match only for corporate firms with at least one employee; thus, the sample for this heterogeneity analysis is almost half of our baseline sample. We present the results in Figure A.15, Figure A.16, and Figure A.17. We can notice how small and medium firms show a small increase for almost a couple of semesters after the pandemic, and then the effect fades away. The effect is widely driven by large firms, whose increment is lagged by one period but spikes up to over 1.5 pp. Large firms appear to be those fitter to deal with the new working arrangements even in non-emergency times.

5.3 Robustness tests

We conducted a robustness check to validate the soundness of our results. We adopted as a dependent variable an alternative measure of WFH, which is continuous and avoids imposing a specific cutoff to classify workers into high and low teleworkable jobs, built as:

$$\text{WFH Index}_{itc} = \left[\sum_j N_{ijct} * \text{ICP Index}_j\right] / N_{it}. \tag{5}$$

For ease of interpretation, WFH Index_{itc} is standardized to have zero mean and unit standard deviation.

WFH Index_{itc} can be interpreted as the average teleworkability of hires done by firm i at time t with the contract type c. We estimated both our DiD[16] and the event-study

[15] We have excluded minings, utilities, and buildings from manufacturing.
[16] Results available upon request.

specifications again. The results of the latter, shown in Figure A.18 in Appendix A on all contract types, are consistent with those of our baseline analysis in Figure 3.[17] This provides evidence in favor of our claim that after the pandemic outbreak, there was a positive shift in the demand for jobs more adaptable to WFH.

Furthermore, we checked if the results could be driven by between-variation across given occupations. To test this, we estimated our model with WFH Share_{iltcg}, where g stands for the macro-occupation category.[18] This specification, by including occupation fixed effects, allows us to take into account specific time-invariant characteristics of each occupation, as long as they are common to 1-digit occupational groups. The results of this estimation exercise (presented in Figure A.19) closely resemble those of our main analysis, thus corroborating our findings and pointing toward an overall increase in the demand for teleworkable occupations that is not driven by between-macro-occupation variation.

We also tested whether our results could be driven by the sample selection and sample trimming criteria that we applied. To verify the robustness of the main findings, we estimated Eq. (4) with two different sample selection rules. On the one hand, we included even shorter contracts that is to say that we excluded from the sample only contracts below 13 days (compared to 30 days used in our baseline estimates); on the other hand, we estimated again our model removing from the sample observations with a total number of hirings exceeding 23 (or the observations in the 99th percentile of the sample). In both cases, the results replicate our main findings very closely.

Lastly, we aimed to exclude that the dynamics of particular regions influenced our main findings. From Figure 1 it is manifest that Piedmont and Lombardy regions had been the most severely hit by COVID-19, hence the intensity of the "treatment" in these two regions could drive the results. We then excluded Piedmont and Lombardy from our estimation and replicated the baseline analysis. Results were once again very close to our baseline estimates.[19]

[17] In addition, we have also replicated all the additional heterogeneity-effect estimations with this continuous measure, and results, available on requests, always hold.

[18] They correspond to ICP 1-digit categories: Legislators, Entrepreneurs, and High Management [1] Intellectual, Scientific, and Highly Specialized Professions [2] Technical Professions [3] Executive Professions in Office Work [4] Qualified Professions in Commercial Activities and Services [5] Craftsmen, Specialized Workers, and Farmers Plant Operators, Fixed and Mobile Machinery Workers, and Vehicle Drivers Unqualified Professions Armed Forces.

[19] Results for all these additional robustness tests are available on request.

6 Before-after comparison

Our identification strategy is only able to capture differences in WFH job creation induced by the differential *intensity* of COVID-19 at the LLM level, leveraging the important geographical variation in COVID-19 spread over Italy. Yet, one potential concern is that COVID-19 might have determined a change in firms' work organization, and correspondingly in labor demand, irrespective of the severity with which they were locally hit by the pandemic shock. To put it in other words, even in LLMs affected by low excess mortality, firms, looking at what happened in highly-affected LLMs, might have started creating more teleworkable jobs. For its nature, our strategy is not able to capture such generalized effects. Thus, in this section, we also report the results of a simple before-after event-study analysis.

Notwithstanding its limitations and strong identifying assumptions, a before-after analysis is useful to highlight potential temporal breaks in WFH job creation that were triggered by the COVID-19 outbreak. We present the results in the form of an event-study specification

$$WFH\ Index_{iltc} = \alpha + \sum_t \beta_t D_t + D_i + D_c + D_s + D_y + \epsilon_{it} \tag{6}$$

which, unlike Eq. (4), does not consider interactions of the period dummies with the excess mortality. Hence, in the figures, the coefficients on the period dummies (and not the interactions with Exc_j) are plotted. We present these estimates only for the baseline specifications in Figure A.20-Figure A.23 in Appendix A, according to the different types of contracts.

Under the before-after identifying assumptions, we should observe that the confidence intervals before the COVID-19 outbreak overlap with zero. This is indeed confirmed in all the figures. The lack of any anticipation effect pre-COVID-19 is hardly surprising given the unexpected nature of the pandemic.

By contrast, a significant increase in the share of teleworkable jobs is evident after the start of the pandemic. As expected, the estimated effects in the before-after analysis are larger than those in our baseline analysis, since they do not exploit the severity of the pandemic, but they simply quantify changes compared to the pre-pandemic period. For instance, in the first semester of the pandemic, the share of teleworkable jobs increased by 0.6 pp, 1.4 pp, and 0.4 pp, for total hires, and hires in permanent and temporary jobs, respectively, compared to the previous semester. Also in the before-after analysis, the effects appear to be transitory, lasting for about three semesters. Although the before-after analysis cannot control for other temporal shocks with exactly the same timing as the pandemic outbreak, it is hard to think of unobserved contemporaneous factors that might have spuriously generated the observed dynamics.

These results highlight how the change in the composition of hires toward more teleworkable jobs has not been solely related to the *intensity* of COVID-19 but also to the *timing* of the pandemic itself.

7 Concluding remarks

The unprecedented shock caused by the COVID-19 pandemic necessitated significant changes in the way firms had to organize their workforce. To sustain production even during the most stringent lockdowns, the adoption of WFH became widespread across all major economies. Firms found it necessary to reorganize their work practices to adapt to this new paradigm, which could have a profound impact on labor demand dynamics.

In this paper, we shed light on firms' capacity to adapt their workforce when confronted with an unprecedented health shock. To this end, we leverage rich Italian data, both from an administrative employer-employee dataset (COB) and a survey on professions akin to the U.S. O*Net, but specific to the Italian labor market (ICP). We employ a DiD-like methodology to assess the impact of the severity of the COVID-19 pandemic, which we proxy using excess mortality at the Local Labor Market level, on the flow of new hires, with a particular focus on jobs that are well-suited for WFH.

Our results demonstrate that comparing two firms in LLMs differing by one-SD in excess mortality, the one in the LLM more heavily affected by COVID-19 experienced on average a 1% larger creation of teleworkable jobs in the post-pandemic period, which rises to 2% when focusing on hirings with open-ended contracts. A DiD-event-study analysis shows the validity of the common trend assumption and that although the effect appears to be transitory and to diminish from the third semester after the onset of the pandemic, the stronger impact found on open-ended contracts suggests that the transformation of the workforce may have been structural. The effects on the first and second semester of the pandemic, especially on permanent contracts, are sizeable, amounting to increases of 2%–4% induced by a one-SD difference in excess mortality. An effect-heterogeneity analysis shows larger effects on younger workers, females, firms located in Northern and partly Southern Italy (compared to the Center), larger firms (above 250 employees), and the service sector.

Given the important shock to the demand for teleworkable jobs documented in our study, we find it of great relevance to analyze how this shift might have further influenced both workers and firms. To do so, a possible development of our work could employ data on wages (e.g., from the Italian National Social Security Institute, INPS) to assess whether because of the higher demand, workers in WFH jobs might have also experienced a wage increase. These further analyses are left for future work.

References

Aksoy, C. G., J. M. Barrero, N. Bloom, S. Davis, M. Dolls, and P. Zarate (2023). Working from home around the world. CEP Discussion Papers 1920, Center for Economic Performance, LSE.

Alfano, V. (2022). COVID-19 diffusion before awareness: The role of football match attendance in Italy. *Journal of Sports Economics 23*(5), 503–523.

Alipour, J.-V., O. Falck, and S. Schüller (2023). Germany's capacity to work from home. *European Economic Review 151*, 104354.

Angelici, M. and P. Profeta (2023). Smart working: Work flexibility without constraints. *Management Science*.

Autor, D. H. and D. Dorn (2013). The growth of low-skill service jobs and the polarization of the U.S. labor market. *American Economic Review 103*, 1553–1597.

Barbieri, T., G. Basso, and S. Scicchitano (2022). Italian Workers at risk during the COVID-19 epidemic. *Italian Economic Journal 8*, 175–195.

Barrero, J. M., N. Bloom, and S. Davis (2021). Covid-19 is a persistent reallocation shock. *AEA Papers and Proceedings 111*, 287–91.

Barrero, J. M., N. Bloom, and S. Davis (2023). The evolution of working from home. Siepr working papers, Stanford Institute for Economic Policy Research.

Bartik, A. W., Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton (2020). What Jobs are Being Done at Home During the Covid-19 Crisis? Evidence from Firm-Level Surveys. NBER Working Papers 27422, National Bureau of Economic Research, Inc.

Basso, G., T. Boeri, A. Caiumi, and M. Paccagnella (2020). The new hazardous jobs and worker reallocation. OECD Social, Employment and Migration Working Papers 247, OECD Publishing.

Berta, P., M. Bratti, C. V. Fiorio, E. Pisoni, and S. Verzillo (2021). Administrative border effects in COVID-19 related mortality. *IZA DP No. 14930*.

Bick, A., A. Blandin, and K. Mertens (2023). Work from home before and after the COVID-19 outbreak. *American Economic Journal: Macroeconomics 15*(4), 1–39.

Bloom, N. (2023). *Golf, rent, and commutes: 7 impacts of working from home*. Stanford, California: Stanford Report.

Bloom, N., P. Bunn, P. Mizen, P. Smietanka, and G. Thwaites (2023). The impact of COVID-19 on productivity. *Review of Economics and Statistics*.

Bloom, N., J. Liang, J. Roberts, and Z. J. Ying (2015). Does working from home work? Evidence from a Chinese experiment. *The Quarterly Journal of Economics 130*(1), 165–218.

Bonacini, L., G. Gallo, and S. Scicchitano (2021). Working from home and income inequality: Risks of a 'new normal' with COVID-19. *Journal of Population Economics 34*(1), 303–360.

Buia, R. E., D. Cavapozzi, G. Pasini, and I. Simonetti (2023). *What is the future of (remote) work?*, Chapter 15 in -Social, health, and economic impacts of the COVID-19 pandemic and the epidemiological control measures: First results from SHARE Corona Waves 1 and 2-, pp. 163–172. De Gruyter.

Buonanno, P., S. Galletta, and M. Puca (2020). Estimating the severity of COVID-19: Evidence from the Italian epicenter. *Plos one 15*(10), e0239569.

Couch, K. A., R. W. Fairlie, and H. Xu (2022). The evolving impacts of the COVID-19 pandemic on gender inequality in the US labor market: The COVID motherhood penalty. *Economic Inquiry 60*(2), 485–507.

Crescenzi, R., M. Giua, and D. Rigo (2022, November). How many jobs can be done at home? Not as many as you think! Papers in Economic Geography and Spatial Economics 27, LSE Geography and Environment Discussion Paper Series.

De Chaisemartin, C. and X. d'Haultfoeuille (2018). Fuzzy differences-in-differences. *The Review of Economic Studies 85*(2), 999–1028.

DeFilippis, E., S. M. Impink, M. Singell, J. T. Polzer, and R. Sadun (2020). Collaborating during Coronavirus: The impact of COVID-19 on the nature of work. NBER Working Papers 27612, National Bureau of Economic Research, Inc.

Dingel, J. I. and B. Neiman (2020). How many jobs can be done at home? *Journal of Public Economics 189*, 104235.

Etheridge, B., Y. Wang, and L. Tang (2020). Worker productivity during lockdown and working from home: Evidence from self-reports. *ISER Working Paper Series* (12).

Feng, Z. and K. Savani (2020). Covid-19 created a gender gap in perceived work productivity and job satisfaction: implications for dual-career parents working from home. *Gender in Management 35*(7/8), 719–736.

Gibertoni, D., K. Y. C. Adja, D. Golinelli, C. Reno, L. Regazzi, J. Lenzi, F. Sanmarchi, and M. P. Fantini (2021). Patterns of COVID-19 related excess mortality in the municipalities of Northern Italy during the first wave of the pandemic. *Health & Place 67*, 102508.

Lee, K. (2023). Working from home as an economic and social change: A review. *Labour Economics*, 102462.

Mongey, S., L. Pilossoph, and A. Weinberg (2021). Which workers bear the burden of social distancing? *The Journal of Economic Inequality 19*, 509–526.

Morikawa, M. (2022). Work-from-home productivity during the COVID-19 pandemic: Evidence from Japan. *Economic Inquiry 60*(2), 508–527.

Msemburi, W., A. Karlinsky, V. Knutson, S. Aleshin-Guendel, S. Chatterji, and J. Wakefield (2023). The WHO estimates of excess mortality associated with the COVID-19 pandemic. *Nature 613*(7942), 130–137.

Tables and figures

Table 1: COB Dataset composition

Characteristic	Frequency	Percent
Permanent Contract	1,179,755	19.52
Temporary Contract	4,128,177	68.81
Other Contract	700,060	11.67
Female	2,744,176	45.74
Male	3,254,817	54.26
Under 35 y.o.	2,764,718	47.38
35-54 y.o.	2,586,390	43.11
55+ y.o.	647,884	10.8
North	2,842,556	47.38
Center	1,179,794	19.67
South	1,976,643	32.95
Total	5,998,993	100

Note: The "other" category of contracts includes: para-subordinate, agency, on call, and apprenticeship contracts. All observations are weighted.
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Table 2: Descriptive statistics of the share of WFH hires

	(mean)	(s.d.)	(25th)	(75th)	(95th)	Obs.
WFH Share all	.188	.373	0	0	1	2,972,342
WFH Share perm	.309	.445	0	1	1	775,521
WFH Share temp	.112	.298	0	0	1	1,786,772
WFH Share other	.305	.434	0	1	1	365,049
WFH Share female	.219	.390	0	.25	1	1,484,584
WFH Share male	.124	.306	0	0	1	1,935,750
WFH Share under 35	.163	.343	0	0	1	1,628,460
WFH Share 35-55	.158	.343	0	0	1	1,551,672
WFH Share over 55	.114	.301	0	0	1	484,028
WFH Share North	.203	.378	0	.142	1	1,477,915
WFH Share Center	.201	.380	0	.066	1	642,148
WFH Share South	.135	.326	0	0	1	1,010,478
Excess Mortality Ratio	13.44	18.05	3.5	16.0	45.3	610[a]

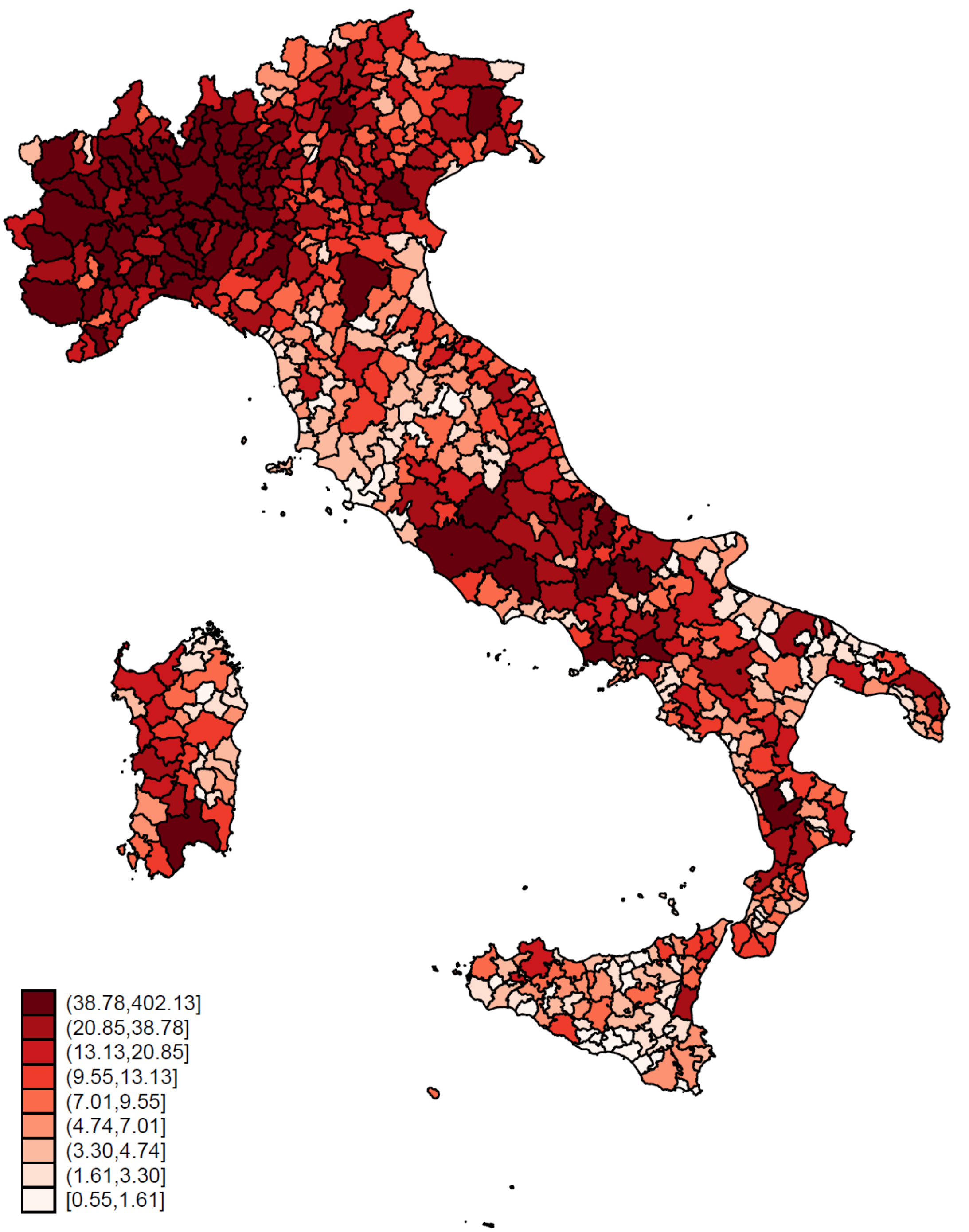
Note: The table reports the mean, standard deviation, and 25th, 75th and 95th percentiles of the dependent variable WFH Share for the whole sample and for different types of contracts and workers' characteristics.
[a]number of LLMs, the geographic unit at which we calculate the excess mortality measure.
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Table 3: DiD Estimation

Dependent Variable:	WFH Share by contract type			
	All	Open End	Fixed End	Other
	(1)	(2)	(3)	(4)
*Exc. Mortality * Post COVID*	.0009***	.002***	.00008	.001
	(.0001)	(.0004)	(.0002)	(.0006)
Firm FE	Y	Y	Y	Y
Contract FE	Y	Y	Y	Y
Period FE	Y	Y	Y	Y
LLM FE	Y	Y	Y	Y
Sector-period FE	Y	Y	Y	Y

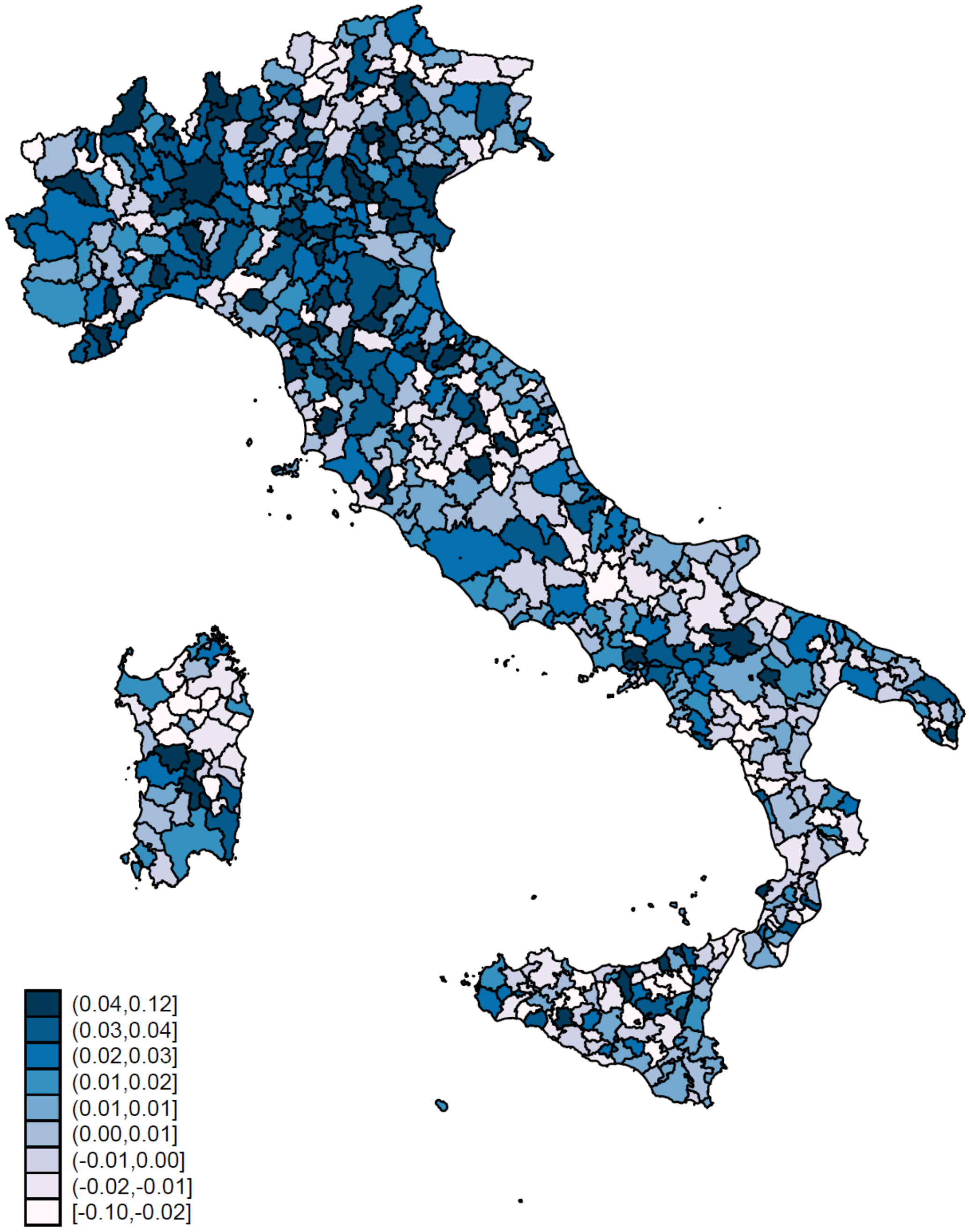
Note: This table reports DiD estimates of Eq. (3). The dependent variable is the WFH Share for different categories of contracts. All kinds of FEs and trends are included. Robust standard errors, clustered at the LLM level in parenthesis. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure 1: Excess Mortality by Local Labor Markets (LLMs)



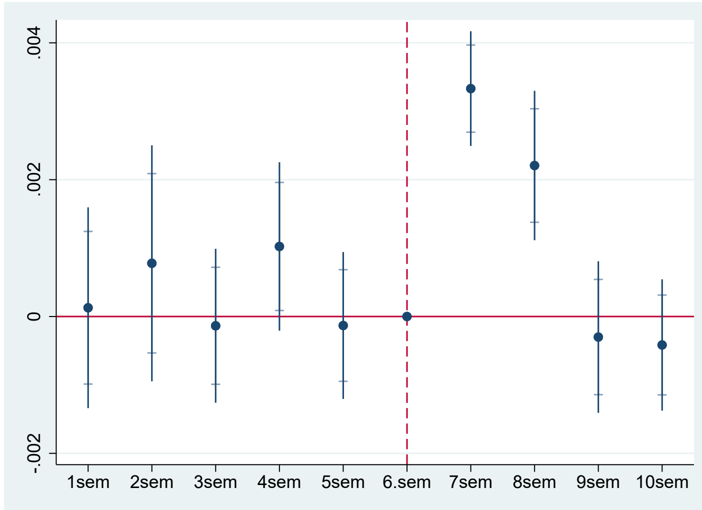
Note: This map displays the excess mortality across all the Italian LLMs, with darker areas representing higher levels of excess mortality. See Eq. (1) for the exact definition of excess mortality.
Source: Authors' elaborations on ISTAT mortality data.

Figure 2: Change in the share of WFH hirings across LLM



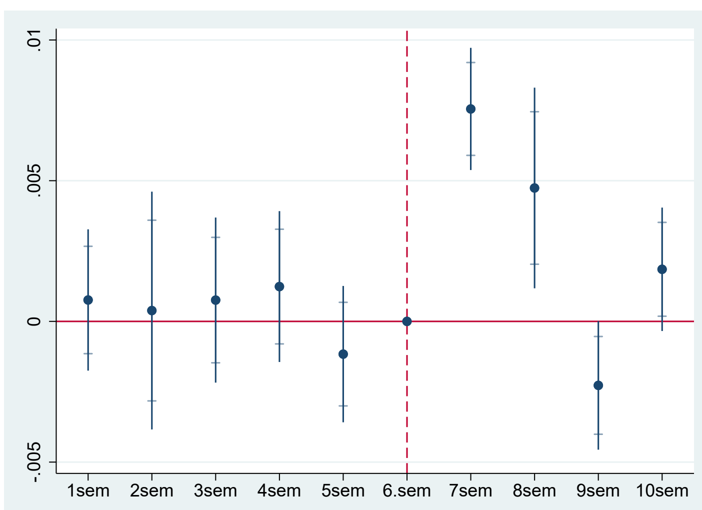
Note: This map displays the difference before and after the COVID-19 outbreak of the dependent variable WFH share of hires, defined in Eq. (2), across all the Italian LLMs, with darker areas representing higher increases.
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure 3: Event Study Estimation WFH - All Contracts



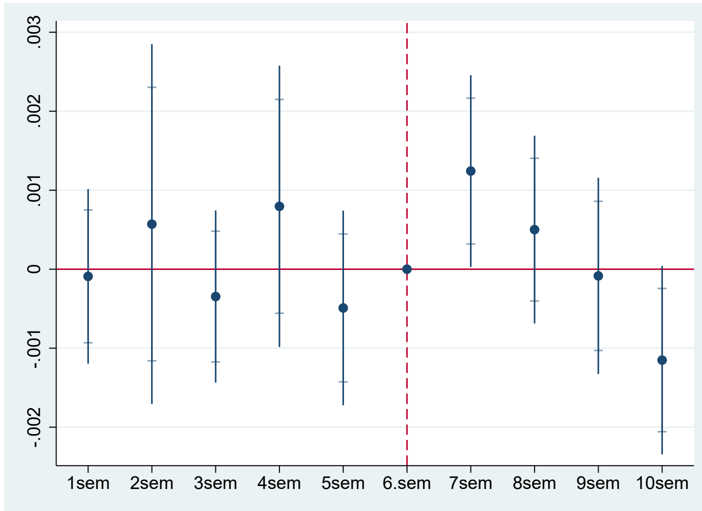
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure 4: Event Study Estimation WFH - Permanent



Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

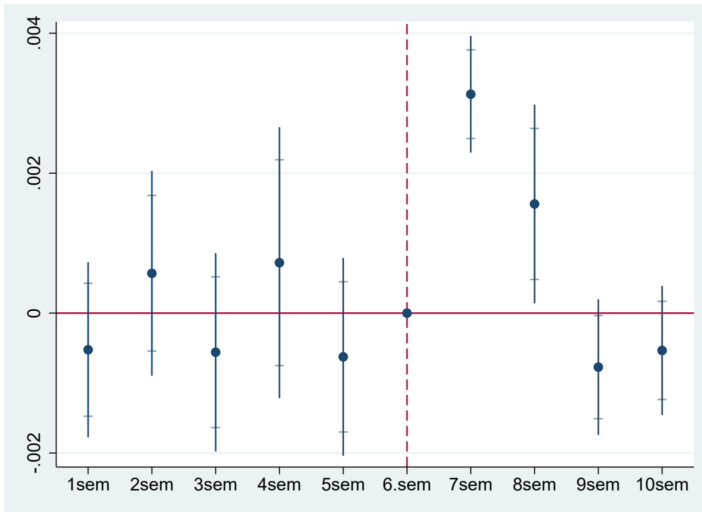
Figure 5: Event Study Estimation WFH - Temporary



Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

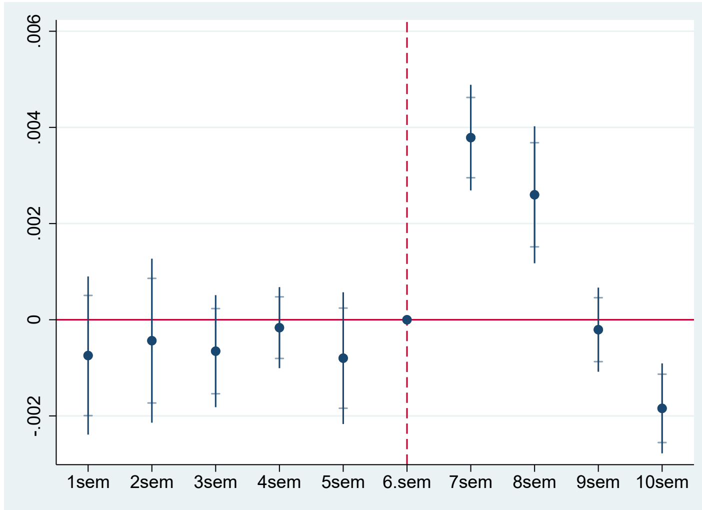
A Additional figures

Figure A.1: Event Study Estimation WFH - Permanent + Temporary



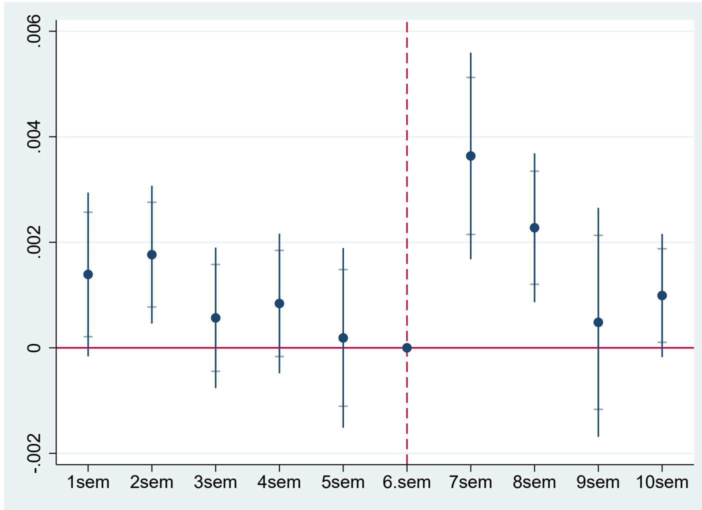
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.2: Event Study Estimation WFH - Males



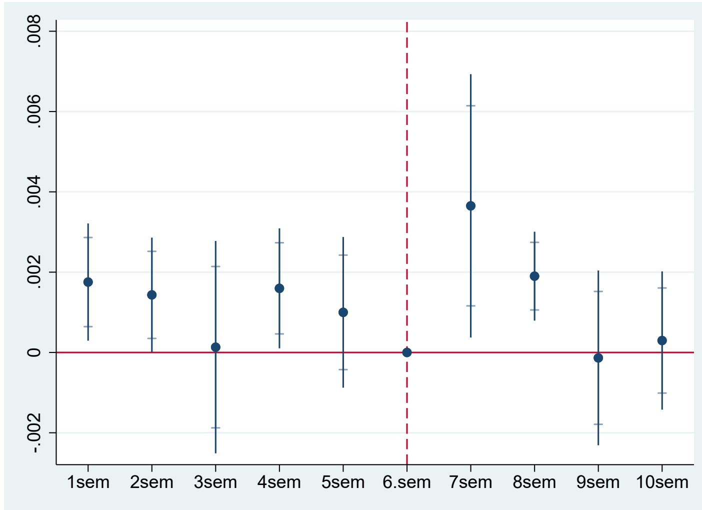
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.3: Event Study Estimation WFH - Females



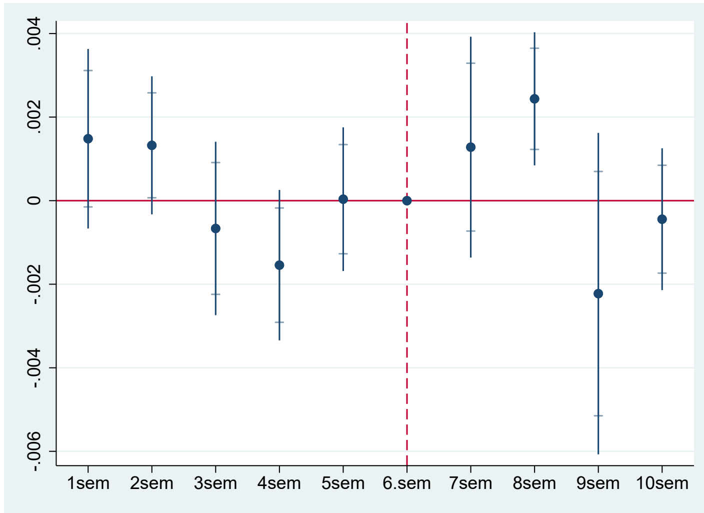
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.4: Event Study Estimation WFH - Females under 35



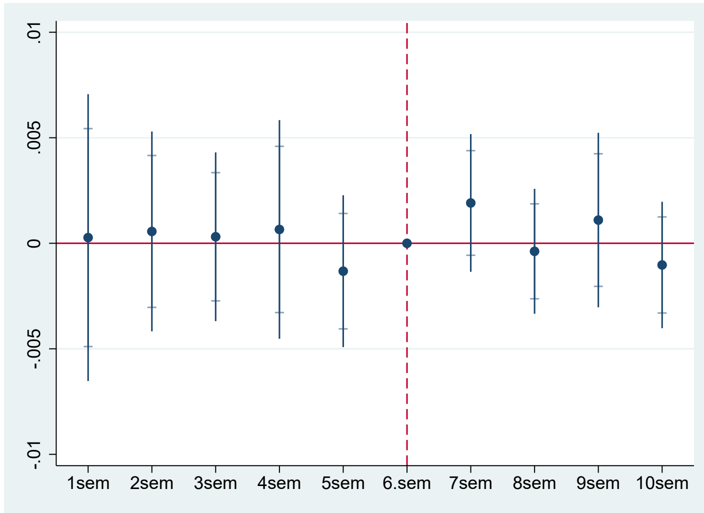
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.5: Event Study Estimation WFH - Females 35-55



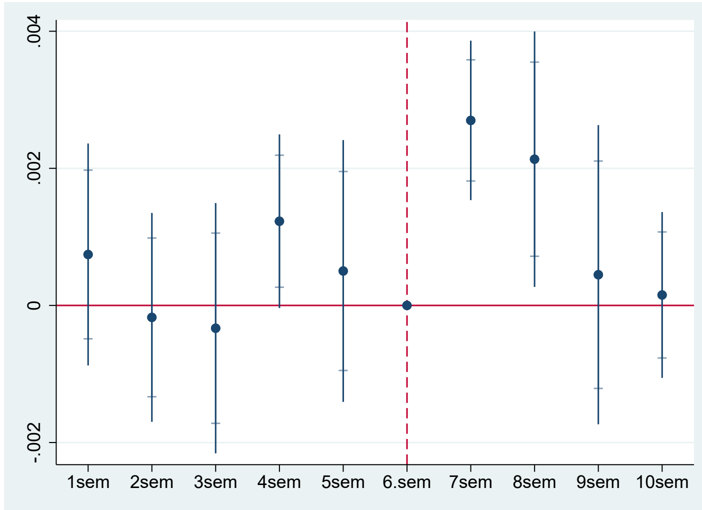
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.6: Event Study Estimation WFH - Females over 55



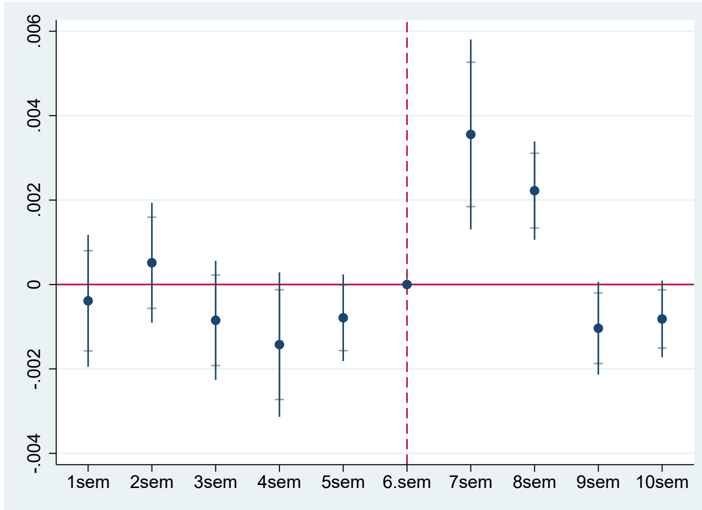
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.7: Event Study Estimation WFH - Under 35



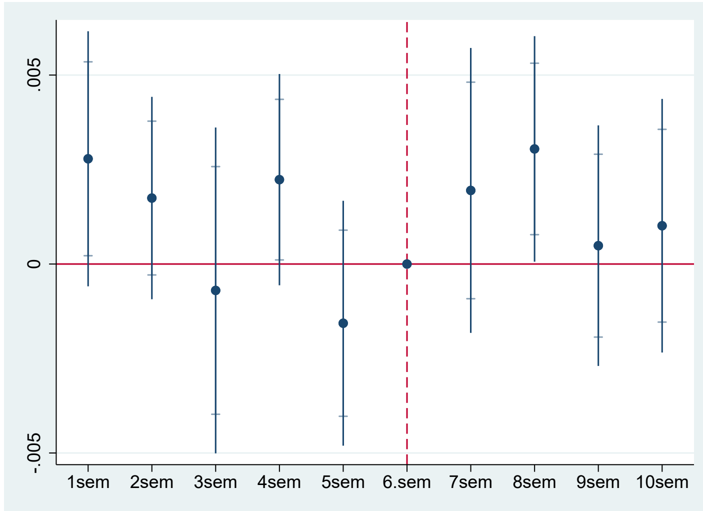
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.8: Event Study Estimation WFH - 35-55



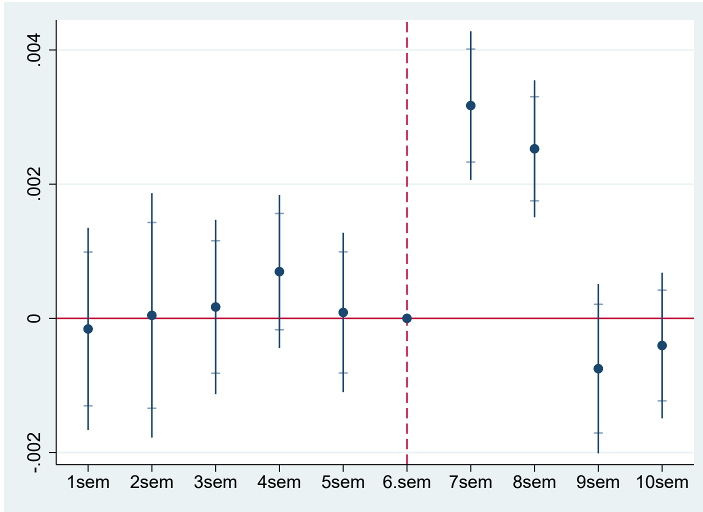
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.9: Event Study Estimation WFH - over 55



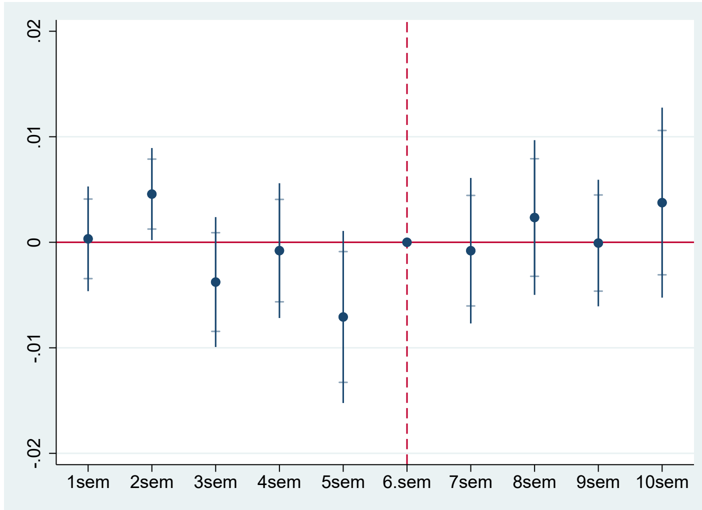
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.10: Event Study Estimation WFH - North



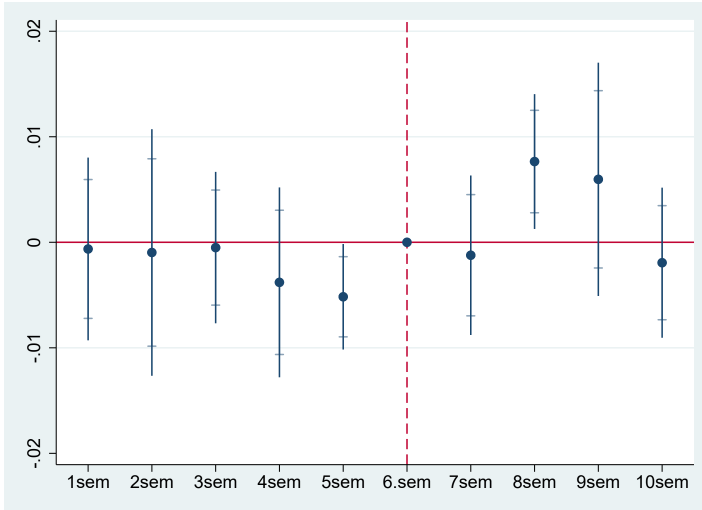
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.11: Event Study Estimation WFH - Center



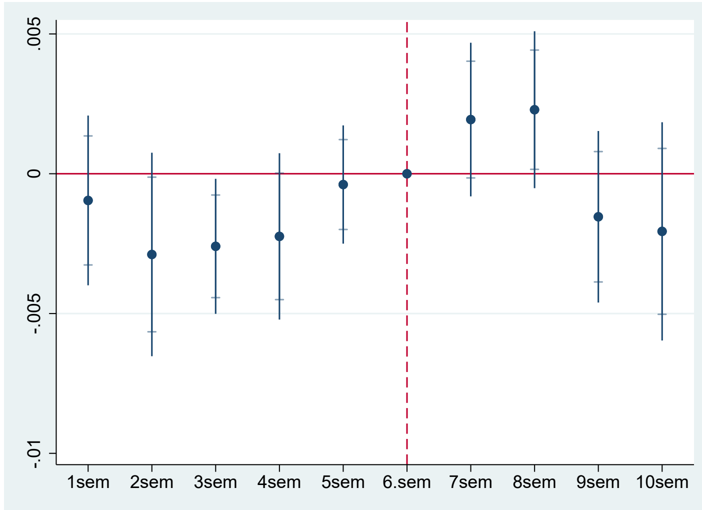
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.12: Event Study Estimation WFH - South



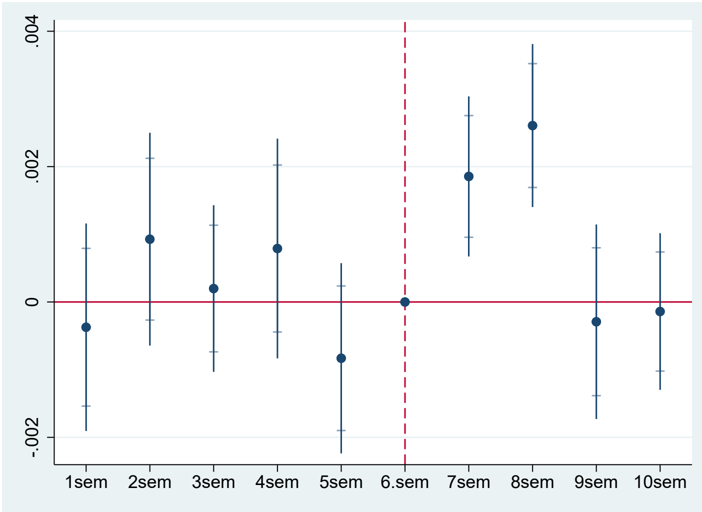
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.13: Event Study Estimation WFH - Manufacturing sector



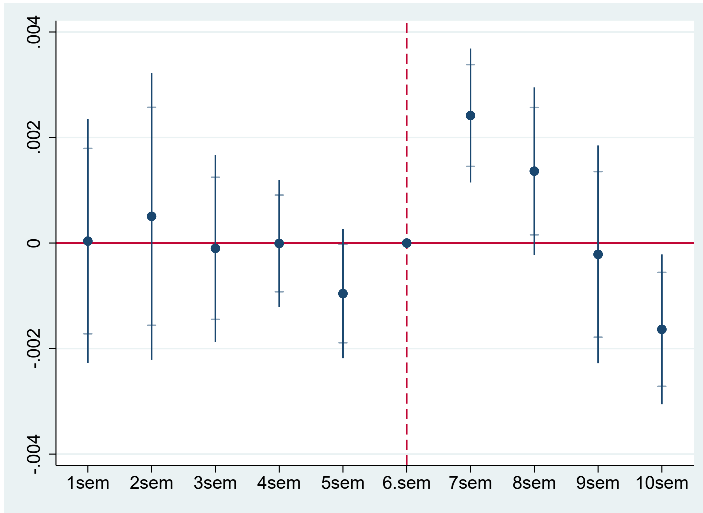
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.14: Event Study Estimation WFH - Service sector



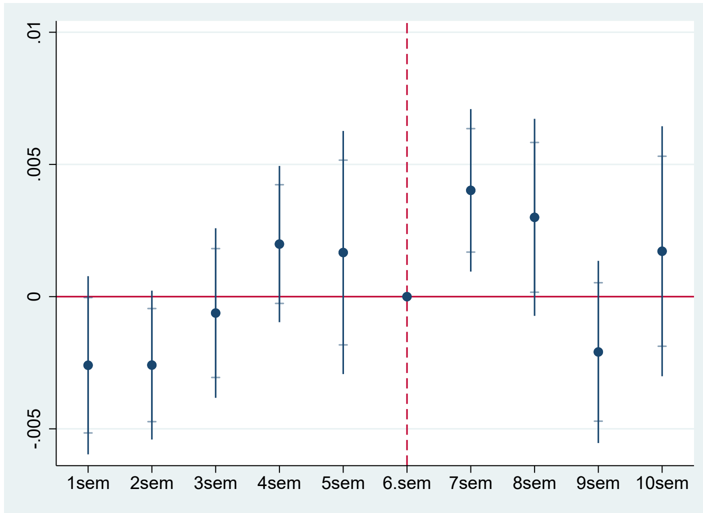
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.15: Event Study Estimation WFH - Small firms (less than 50 employees)



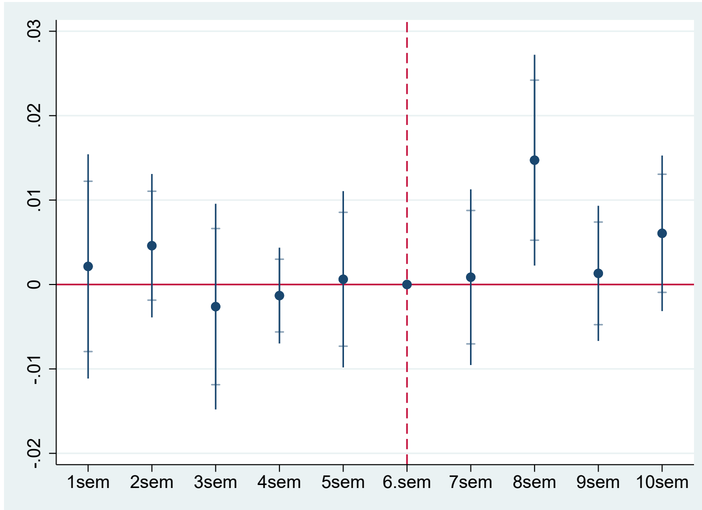
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.16: Event Study Estimation WFH - Medium firms (50-250 employees)



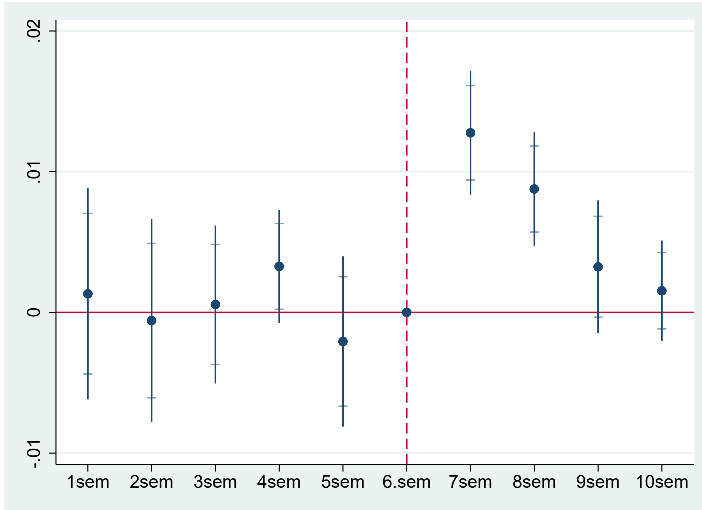
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.17: Event Study Estimation WFH - Large firms (more than 250 employees)



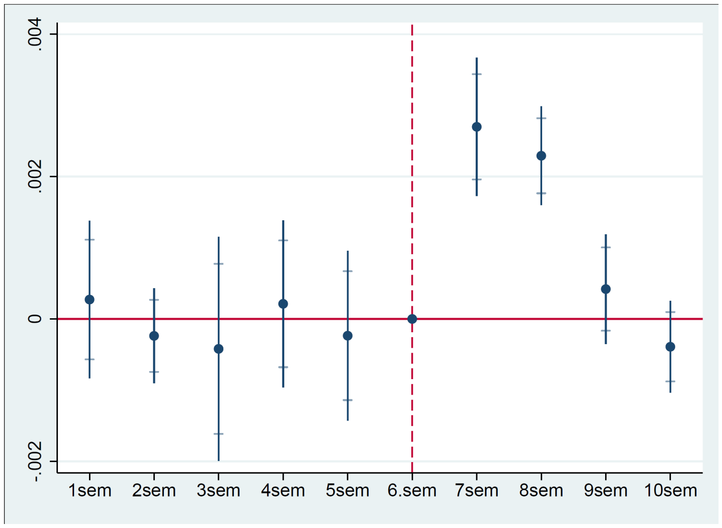
Note: This figure displays the estimated coefficients β_t of Eq. (4). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.18: Event Study Estimation - Continuous WFH measure



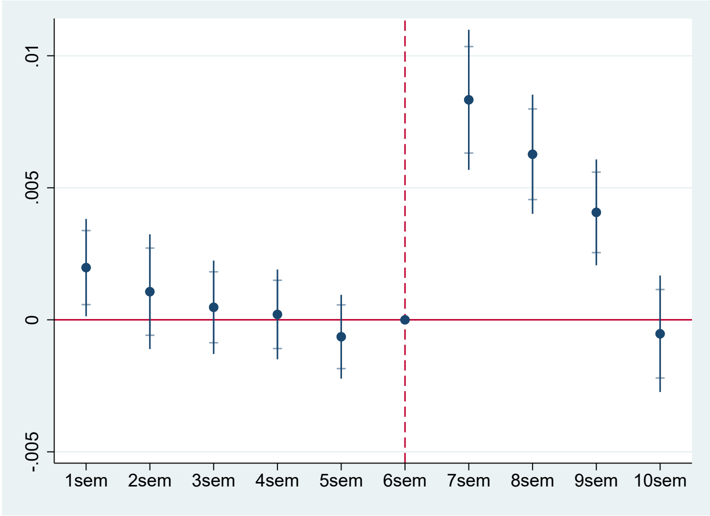
Note: This figure displays the estimated coefficients β_t of Eq. (4), adopting as dependent variable a standardized, continuous indicator. The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.19: Event Study Estimation - Macro Occupation FEs



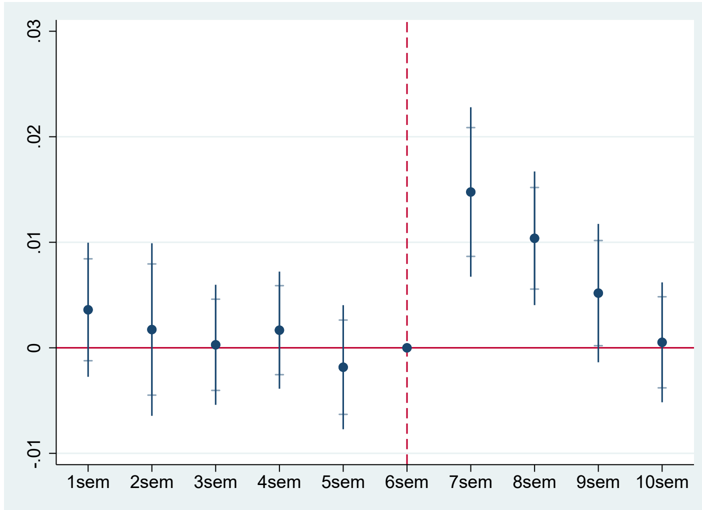
Note: This figure displays the estimated coefficients β_t of Eq. (4), including macro occupation FEs. The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.20: Before-After Analysis - All Contracts



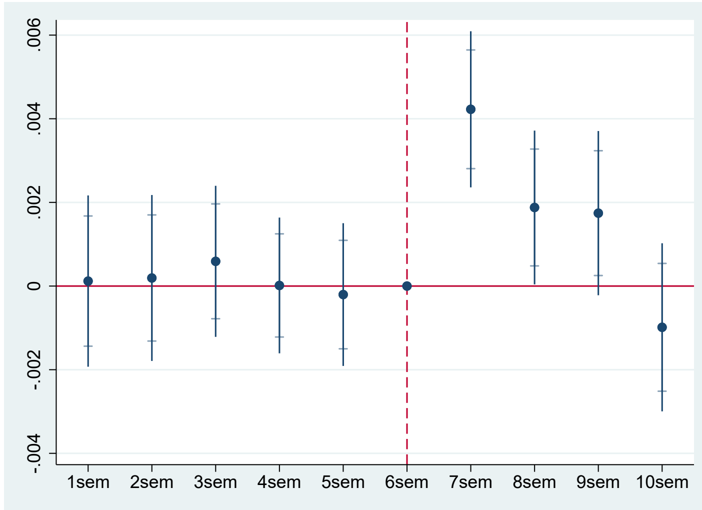
Note: This figure displays the estimated coefficients β_t of the before-after analysis Eq. (6). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.21: Before-After Analysis - Permanent



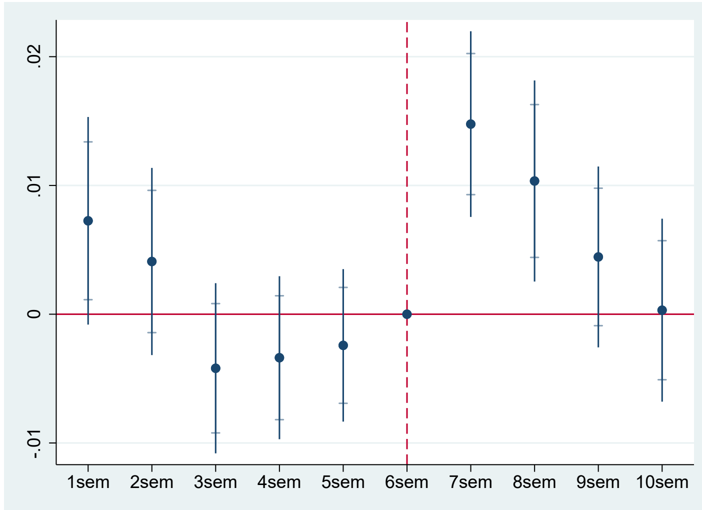
Note: This figure displays the estimated coefficients β_t of the before-after analysis Eq. (6). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.22: Before-After Analysis - Temporary



Note: This figure displays the estimated coefficients β_t of the before-after analysis Eq. (6). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.

Figure A.23: Before-After Analysis - Other



Note: This figure displays the estimated coefficients β_t of the before-after analysis Eq. (6). The spikes represent the 95% confidence intervals, and the lines the 99% confidence intervals based on standard errors clustered at the LLM level. On the horizontal axis is reported the timing, from the 1st semester of 2017 (1sem) to the 2nd semester of 2021(10sem); the reference period is the second semester of 2019 (6sem).
Source: Authors' elaborations on COB-ICP dataset 2017-2021.