The Wage and Mobility Effects of Remote Work*

Francesco Alosa[†], Laura Khoury[‡], Youssef Souidi[§]

February 20th, 2026

Abstract

The shift to remote work, with roots predating Covid-19, marks a major transformation of labor markets. This paper investigates its medium-run impact on workers' labor market outcomes, exploiting plant-level variation in remote work agreements implemented between 2014 and 2017 in France. Using an event study design and rich administrative data, we find that access to remote work yields moderate wage increases and facilitates geographical mobility with increases in commuting distance. Examining mechanisms, we find that workers moving to new plants that also have adopted remote work experience larger increases in commuting distance, along with upward occupational mobility. This pattern suggests that remote work options alleviate job search constraints, allowing workers to seek higher-paying and possibly higher-ranked jobs. Our analysis further reveals that plant-level remote work agreements raise firm productivity, benefiting both incumbent and newly hired workers. Overall, our results underscore how remote work reshapes labor market trajectories through its effects on mobility, job search, and productivity.

Keywords: remote work, geographical mobility, occupational mobility, productivity.

JEL codes: J16, J24, J61, J62.

*The authors would like to thank participants at several university seminars and conferences for their valuable feedback and suggestions.

[†]ISEG - Lisbon School of Economics and Management, Universidade de Lisboa; Uppsala Center for Fiscal Studies (UCFS). Email: francesco.alosa@iseg.ulisboa.pt.

[‡]Paris-Dauphine University, PSL University, LEDA, CNRS, IRD, LEGOS, 75016 PARIS, FRANCE. Email: laura.khoury@dauphine.psl.eu.

[§]Institut des Politiques Publiques. Email: youssef.souidi@ipp.eu.

1 Introduction

Remote work expanded dramatically following the Covid-19 pandemic, reshaping modern labor markets. In the U.S., the proportion of work-from-home (WFH) days surged from 7% in 2019 to nearly 60% in the spring of 2020, before stabilizing around 28% by 2023 (Barrero et al., 2021, 2023). Initially driven by social distancing mandates, remote work has also long been advocated as a tool for achieving better work-life balance. Yet despite its rapid and widespread adoption, we still know relatively little about the medium- to long-run effects of WFH on workers' labor market trajectories. This paper fills this gap by studying the consequences of access to remote work for workers' wages, mobility, and productivity up to three years after implementation, drawing on quasi-random plant-level variation in the adoption of WFH arrangements. We also explore mechanisms through a rich heterogeneity analysis. Our focus is on the pre-Covid period, as pandemic-era remote work may not represent WFH practices in a stable environment.[1]

Theoretically, the impact of WFH arrangements on wages is ambiguous. Remote work is typically viewed as a valued job amenity, yet its implications for wage setting are not straightforward. For example, Mas and Pallais (2017) find that the average worker is willing to forgo 8% of their wage for the option to work from home, and up to 20% to avoid an employer-dictated fixed schedule. Employers might leverage this "taste for flexibility" to moderate wage growth within firms. On the other hand, WFH arrangements could influence productivity, with emerging research finding mixed results. In the long run, these wage effects may also depend on how limited workplace interactions impact promotion prospects (Cullen and Perez-Truglia, 2023) and whether workers factor the remote work amenity into their job search decisions. Understanding these channels requires examining not only wages but also occupational and geographical mobility, as well as productivity.

These effects could be heterogeneous, particularly along gender lines.[2] Commuting constraints and regular work schedules disproportionately limit women's job search options, contributing to persistent gender wage gaps (Goldin, 2014; Le Barbanchon et al., 2020; Butikofer et al., 2023; Bergemann et al., 2024). WFH could relax these constraints and expand women's access to higher-paying jobs, but it could also operate as a substitute for other job amenities, yielding little net impact on wages. Experimental evidence suggests that women have a higher willingness to pay for remote work than men (Mas and Pallais, 2017). Time-use studies further suggest that the time freed by WFH is allocated

[1] A significant share of workers were already using remote work on a weekly basis before Covid-19. The American Time Use survey shows that 10% of US wage and salary workers had at least 1 workday over a 2-week period when they worked from home in 2017-2018. Figure A1 also reports a significant remote-work takeup rate in Europe in 2015. In France, almost 5% of employees were regularly working from home, and another 21% were using ICT for the purposes of work outside the employer's premises.

[2] For instance, Aksoy et al. (2025) documents that access to remote work encourages women's labor force participation in Turkey. Conversely, Wielgoszewska et al. (2024) find that working from home is more detrimental to women's mental health during the COVID-19 pandemic in the UK.

differently across genders: women often increase home production, some of which occurs during core working hours (Pabilonia and Vernon, 2022). Gibbs et al. (2023) also find that WFH has a more negative effect on women's productivity, as household responsibilities (not necessarily childcare) occupy part of their working hours. These patterns underscore the need to examine how WFH affects different groups of workers who trade off wage, commuting time, and remote work differently.

Our empirical strategy exploits a 2012 law in France that created a formal legal framework for remote work, requiring that WFH be voluntary and mutually agreed upon while clarifying employers' obligations. Following the law, many plants negotiated agreements specifying WFH conditions. We exploit the staggered timing of these plant-level agreements between 2014 and 2017 in an event-study design. Our methodology combines multiple administrative data sources: first, we use data on plant-level agreements between the employer and employees over the 2014-2017 period. A treated firm is defined as a firm where a remote-working agreement is signed. Second, we use the Labor Force Survey (*Enquete Emploi*) to measure teleworking take-up among workers in treated firm. Third, we use matched employer-employee data with an exhaustive panel of the working population in France between 2009 and 2019. This allows us to identify treated individuals working in the treated plants, and to track workers over time and across plants from four years before the signature to three years after.[3] Moreover, part of the matched employer-employee dataset is matched with demographic information (*Echantillon Démographique Permanent*), e.g. number of children. This information is especially valuable for exploring the role of domestic work constraints in mitigating or amplifying the effect of WFH arrangements. Then, we exploit within-plant across-individual variation in the probability to work from home by building a prediction model of the probability to work from home, based on a rich set of covariates, that we train on the labor force survey data. Finally, we employ firms' balance sheet data to explore the effects of WFH arrangements on productivity.

Our paper presents three main findings. First, access to remote work generates modest but positive wage gains of about 2.4% within the first two years of adoption.[4] Second, remote work increases productivity and can foster both occupational and geographical mobility. Third, these effects are stronger for workers who change workplaces after adoption, especially if they move to a treated plant, and for those in occupations with a high predicted probability of working remotely. Together, these results point to two central mechanisms: (i) WFH enables workers to expand the scope of their job search, and to seek higher-paying jobs; (ii) WFH increases productivity for both incumbent and newly hired workers.

[3] However, to keep a more balanced sample, we examine outcomes up to two years after the signature of the agreement for most outcomes.

[4] This positive effect is consistent with the fact that most remote work arrangements are hybrid in France (Askenazy et al., 2025), and hybrid arrangements are usually associated with productivity gains.

Our paper contributes to the literature on the effects of WFH on wages. The evidence on this topic is somewhat mixed, depending on the type of WFH arrangements that are considered, the type of job and the skills involved, and the compatibility of these jobs with WFH arrangements. While hybrid arrangements, which allow workers to work from home a few days a week, are shown to have either null or positive impacts on productivity (e.g. Bloom et al. (2015, 2022); Choudhury et al. (2021); Angelici and Profeta (2024); Boeri and Rigo (2025)), working full-remote can harm productivity especially if the jobs involved require coordination among workers and teamwork (e.g. Gibbs et al. (2023); Emanuel and Harrington (2024)). The negative effects on productivity tend to be stronger for newer and inexperienced workers who are less likely to attend training sessions and have meetings with managers when working full remote (Emanuel and Harrington, 2024). We contribute to the literature by examining the medium-run effects of WFH arrangements, up to three years post-implementation, and by examining a broad range of occupations.[5] This matters because the immediate impacts of WFH on wages, driven by changes in productivity, are likely to differ from longer-term effects, during which workers may adjust their job search behaviors, change jobs, or receive promotions. Additionally, we tentatively explore the role of these different channels by investigating outcomes beyond wages and by assessing heterogeneous effects.

Our paper also adds to the literature exploring how the shift to remote work has reshaped local labor markets and locality choices. Consistent with our results, Coskun et al. (2024) find that the shift to remote work induced an increase of commuting distance in Germany. Boeri and Rigo (2025) focus on the case of France and measure a post-pandemic increase in commuting distances compared to the pre-pandemic period. This increase in commuting distances, primarily driven by firms hiring workers living farther away, led to gains in value-added, productivity and hours worked at the firm level. Similar to Boeri and Rigo (2025), we extend previous literature by looking at nationwide effects, instead of focusing on a single firm. However, our analysis focuses on individual workers rather than firm performance. We dig deeper into the mechanisms underlying workers' wage responses by tracing their occupational and geographical mobility beyond their initially assigned plant. Importantly, our results are based on the pre-Covid period, providing evidence from an environment closer to a steady state of remote-work adoption rather than a pandemic-driven shock.

Finally, our findings speak to the literature on job amenities, highlighting how different workers prioritize different features when looking for a job. Research has shown that, due to unequal household responsibilities, women are generally more willing than men to trade off wages for benefits such as reduced commuting time, more predictable schedules, and lower workplace risks, including sexual harassment (Goldin, 2014; Le Barbanchon et

[5] Most of the existing studies are randomized controlled experiments focusing on one firm, and often on one particular occupation (e.g. call-center workers, patent examiners, etc.).

al., 2020; Butikofer et al., 2023; Bergemann et al., 2024; Collis and Van Effenterre, 2024). For instance, Le Barbanchon et al. (2020) document that around 10% of the gender wage gap in France is accounted for by differences in the WTP for a shorter commute. The option to work from home, could, in theory, alleviate many of these constraints. Experimental evidence shows that, indeed, women value WFH more than men if it is to avoid workplace hostility (Collis and Van Effenterre, 2024). Whether WFH arrangements will enable women to access higher-paying positions, or if this amenity will merely replace existing ones, remains an open question. This paper also tries to answer this question.

The remainder of the paper proceed as follows: section 2 presents the institutional set-up by describing the remote work legislation, the different data sources being used, and how the sample of interest is constructed; section 3 describes the empirical strategy; section 4 presents the main results; section 5 describes the mechanisms driving the main results by presenting the heterogeneity analysis, and provides an additional analysis at the firm and plant levels; section 6 concludes.

2 Institutional Background and Data

2.1 Remote Work Legislation

Remote work was introduced in the French Labor code on March 22, 2012, with Law n. 2012-387. This legislation sets the legal framework of remote work, which is defined as "Work whose activities are carried out away from the company's site" (JORF n°0071 of march 23, 2012, Law n° 2012-387 of march 22, 2012). Remote work is voluntary and based on agreements between the employer and the employees. These agreements are typically signed by delegates of the workers' union. A refusal to telework by the worker cannot be sanctioned in any way and it cannot be a valid motivation to terminate the worker's employment contract. An employee who desires to work from home can be offered a work-from-home arrangement by the employer provided that the company fund the material costs related to WFH (e.g. computer, screen, headset, microphone) and the task is compatible with off-site work. When working from home, the employee retains all her salary rights, as if she worked on site. The remote worker is therefore insured in case of any accident during her working hours at home, and has the right to "disconnect" outside working hours. To adopt WFH arrangements, the employer needs to set clear eligibility criteria to allow employees equal access to remote work. Once the agreement is stipulated, the employer cannot force the employee(s) to return to the office full-time without a valid motivation. However, remote workers can resume work on the plant's premises if they wish to do so in line with the terms of their employment contracts. The 2012 legislative change triggered a wave of plant-level agreements outlining specific conditions for WFH arrangements.

2.2 Data

We employ several databases to conduct our analysis. First, we use data on plant-level agreements between the employer and employees over the 2014-2017 period (the *D@accord* database). A treated plant is defined as an plant where a remote-working agreement is signed. Second, we use the Labor Force Survey (the *Enquete Emploi* data) to measure teleworking take-up among workers in treated firm. Third, we use matched employer-employee data with an exhaustive panel of the working population in France (the *DADS* data).[6] This allows us to identify treated individuals working in the treated plants, and to track workers over time and across plants throughout the 2009-2019 period. Moreover, part of the matched employer-employee dataset is linked to demographic information (*Echantillon Démographique Permanent*), e.g. number of children, which allows us to conduct additional heterogeneity analysis based on marital status and number of children. Fourth, we employ firms' balance sheet data (*FARE*), containing detailed info on turnover, assets, investments, costs and profitability. A treated firm is defined as a firm where at least one plant signed a remote-working agreement.

2.3 Sample construction

We start by identifying the plants which signed an agreement regulating working from home arrangements between 2014 and 2017. Using the plant identifier (*SIRET*), we link these plants to their workers in the labor force survey as well as in the matched employer-employee database. If a plant has signed several WFH agreements over the period, we consider the first one as the *event*.

The labor force survey is used to measure WFH takeup, and test whether it changes after the signature of an agreement at the plant level (Section 4). The matched employer-employee data is used to measure the effect of working in a firm that signed an agreement on labor market trajectories. We use data from 2009 to 2019 to observe at least 5 years before the treatment and 2 years after. To measure these effects, we need to consider a control group of comparable workers who are working in plants without a teleworking agreement. In the baseline analysis, we focus on the sample of ever-treated individuals, in which we use individuals in plants that have not yet signed an agreement as controls

[6] This panel is built from the exhaustive cross-sectional matched employer-employee data, the *DADS Postes*. We rely on the code provided by Babet et al. (2022) to convert this cross-sectional data into a panel data, exploiting overlapping information from one yearly dataset to the next. The limitation of this method is that we loose track of individuals who are non-employed for at least a full year. They might reappear in the data, but we would not be able to link them to their initial identifier. This is not a strong limitation in our case since (i) we start from a sample of employed individuals with a strong attachment to the labor market; (ii) we check that the treatment itself has no differential impact on the probability to leave the data between treated and controls (A21). This check is performed on a panel provided by the Ministry of Labor for 1/12th of the working population in France, that does not suffer this limitation. We see very little difference in the probability of leaving the dataset by treatment status after the treatment.

for individuals in plants in which such agreements were already signed.[7] Moreover, we restrict the sample to individuals who work in the same firm in the four years preceding the signature, to avoid self-selection into plants that are about to be treated. We end up with 306,569 individuals followed from 2009 to 2019, working in 1821 plants.

3 Empirical Strategy

We conduct an event-study analysis that exploits the variation in the probability of working from home stemming from the signature of collective agreements at the plant level. As such, the treatment is at the plant level. The event study leverages variation in the date of the treatment between 2014 and 2017. It uses a control group of plants that have not yet signed an agreement on working from home arrangements. We estimate the following equation:

$$Y_{i,j,p,t} = \alpha_i + \sum_{\substack{j=-4 \\ j \neq -1}}^{2} \beta_j Dist_j + \gamma_t + \lambda_{s,t} + \epsilon_{i,j,p,t}, \tag{1}$$

with $Y_{i,p,t}$ is the outcome variable (e.g. hourly wage) in year t for individual i in (reference) plant p; $Dist_j$ the set of dummies measuring the distance to the event in years; α_i worker fixed effects; γ_t calendar year fixed-effects; $\lambda_{s,t}$ 1-digit sector-level trends. Worker fixed-effects account for the time-invariant unobserved differences between workers in firms which signed an agreement and workers in firms which did not sign an agreement. Year fixed-effects account for time trends that are common to the whole sample, and 1-digit sector-level time trends account for time trends that are common to all firms in each sector. The identifying assumption is therefore that early-treated workers would have followed a similar wage trend than late-treated workers (i.e. the timing of the signature is random in a 4-year window). To estimate Eq. 1, we use the De Chaisemartin and d'Haultfoeuille (2020) estimator that is robust to heterogeneous treatment effects. We cluster standard errors at the level of the reference plant (i.e. the plant where individuals are employed in the pre-event years).[8]

The balance table for early versus late-treated workers (Table A1) presents some descriptive statistics on individuals by treatment cohort, showing they are quite similar along most observable dimensions. Early and late-treated individuals have a similar gender composition, average age and mostly have full-time contracts with similar contract duration. Both early and late-treated individuals are very concentrated in large urban areas, and in some specific occupations such as private-sector white collar jobs (*Cadres*

[7]For the analysis on ever-treated individuals, we additionally include the 2018-2019 agreements as control cohorts.

[8]We also test that our results are robust to using alternative estimators, such as Callaway and Sant'Anna (2021).

d'entreprise) and clerical and commercial intermediate professions (*Professions intermédiaires administratives et commerciales des entreprises*). This similarity brings credibility to the assumption that outcomes for early-treated would have evolved the same way as late-treated workers, if they had been part of a late-treated plant. Moreover, focusing on ever-treated workers allows a good comparability of treated and controls units also in terms of unobservables. However, they also differ in some dimensions, such as average gross earnings level and growth rate. Additional evidence is brought by the inspection of the pre-event trends.

Another potential concern is that the signing of WFH agreements may have coincided with other organizational changes that could independently affect workers' labor-market trajectories. We address this issue in two ways. First, we check that WFH agreements are not embedded within broader agreements that cover topics likely to influence wages. In particular, we exclude all agreements related to wages and bonuses, gender equality, working hours, mobility, work-life balance. Second, we examine whether the composition of workers at the plant level changed around the time of the agreement. Although our sample of treated workers is restricted to incumbents (i.e., those employed at the plant for at least four years prior to the signature), to ensure that workers do not self-select into a plant about to adopt WFH arrangements, shifts in workforce composition could still reveal simultaneous organizational changes. Figures A22–A25 in Appendix A show no meaningful change in worker composition, alleviating this concern.

4 Results

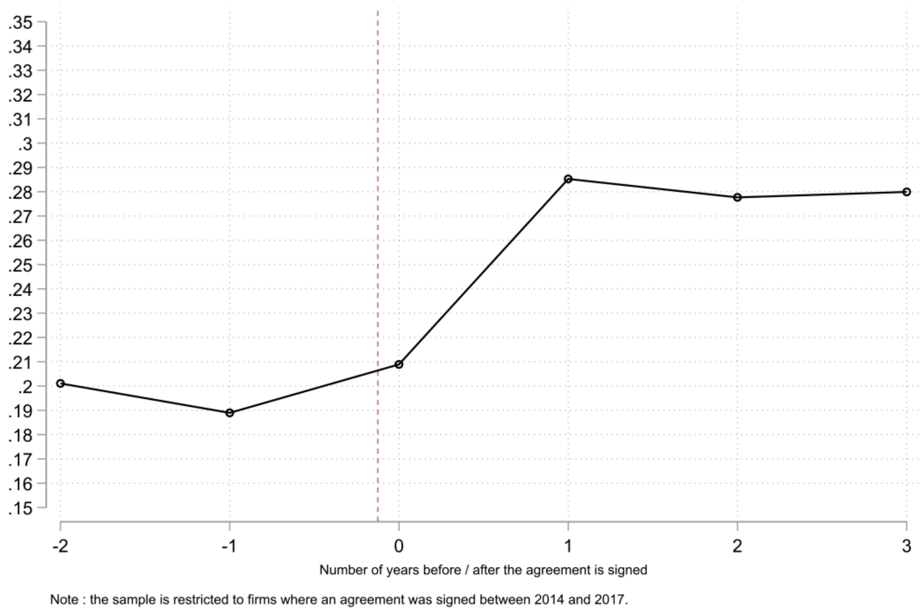
The Effect of WFH Agreements on WFH Takeup. In this section, we use data from the Labor Force Survey (LFS) to check that workers in treated plants react to the signature of a remote work agreement. WFH takeup can only be measured in survey data, and is not recorded in the matched employer-employee data. Using plant identifiers, we can link treated plants to their workers surveyed in the LFS. In the LFS, workers are asked if they sometimes work from home.

Figure 1 shows that while the share of workers reporting working regularly from home is stable before the signature of an agreement in the plant, it jumps by nearly 9 ppts (47%) the year following the signature, compared to the year before the signature.[9] The takeup rate stays relatively stable the following years, indicating that the shock occurs right after

[9]Note that the share of workers WFH seems a little bit high. This is because of the slight ambiguity in the way the question is asked. It could be interpreted as whether workers were taking work home and working from home outside regular working hours, or in the more traditional sense of working remotely, outside the firm premises. Since 2021, the question has been clarified to strictly include remote work. For the years were both questions are available, although the levels of the share of respondents answering positively are different, the trends are very similar. Since we are interested in the change in the level here, this ambiguity should not affect the results. If anything, the relative effect in terms of % increase might be underestimated.

the signature of the agreement. Figures A3 to A5 illustrate the variation in the takeup rate and the response to the signature by socio-demographic groups. While the initial takeup rate was higher among men, the response to the signature of the agreement is larger for women (nearly 59% vs 42% one year after the signature). Conversely, the initial takeup rate was lower for workers without children, but they experience a larger increase in takeup after the signature (nearly 71% vs 20%). Finally, the takeup rate is almost zero for blue-collar workers, in line with the limited teleworkability of their occupations, while it is already as high as 30% for white-collar workers the year before the signature. They experience a 15 ppts increase in their probability to work from home at least once in the last four weeks following the signature of a plant-level agreement. These findings are reassuring that the agreements are being put into practice. It also indicates that for some categories, such as women or white-collar workers, the takeup rate is strongly reacting to the treatment.

Figure 1: Share of workers WFH in the last 4 weeks



NOTE: This graph plots the share of employees reporting having worked from home in the last 4 years in plants that signed a WFH agreement between 2014 and 2017.

Main results. We estimate equation 1 on the logarithm of hourly wage, occupational mobility and commuting distance. Figures 2 to 4 report the β_j coefficients from the estimation of Eq. 1 on these outcomes. We observe a moderate gain in the treatment year and the two following years for workers in early-treated plants compared to workers in not-yet-treated plants. This increase is equivalent to about a 2.4% gain on hourly wage in the year following the signature. We reproduce the analysis on hourly wage in levels in Appendix A. Figure A6 displays a larger effect on hourly wage, equivalent to almost a 10% increase one year after the signature. These results strengthen the idea that having the option to work from home induced some wage gains. Figures A7-A8 seem to indicate that this is driven mostly by an increase of gross earnings, as the decrease in working hours is small and not statistically significant at the 5% level.

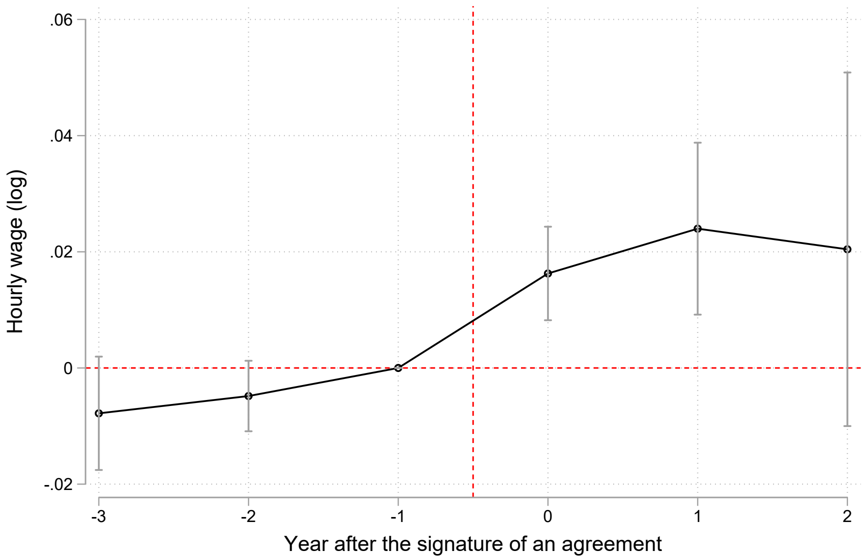
The moderate wage gains could be driven by three different channels: (i) an increase in productivity at the firm level; (ii) a broader set of searched jobs associated with higher wages; (iii) promotions. To disentangle between these mechanisms, we test additional outcomes. We first investigate whether, at the individual level, wage gains are associated with occupational mobility. We compute the median hourly wage at the 2-digit occupational level using the universe of employment spells over 2009-2019, and rank occupations according to their median hourly wage. We then assign to each worker in our sample the rank of their occupation every year. Figure 3 shows no significant change in occupational rank after the signature of a WFH agreement.

Moreover, figure 4 shows that workers having the option to work from home see their commuting distance increase after the treatment relative to control workers ($\approx$ +3% one year after the signature relative to mean outcome one year before the event).[10] This set of results suggests that mechanism (ii) at least partly explain the wage gains. While workers broaden their search for higher-paying jobs, having the option to work remotely is, in most cases, not sufficient to climb the occupational ladder. Since we are, at the moment, only exploiting variation in the probability to work from home at the plant level, we are limited in our exploration of intra-plant outcomes (such as internal promotions for instance). The next section further explores the underlying mechanisms in two ways: (i) we run a heterogeneity analysis by gender, by whether workers changed firm two years after the treatment, and by whether they have children; (ii) we exploit within-plant across-individual variation in the predicted probability to work from home, which allows us to augment Equation 1 with plant fixed effects. This specification is used to test mechanisms that would apply within plants, and also to support the idea that our findings are driven by the WFH arrangements, controlling for all other plant-level changes that could have happened at the same time. Finally, we also investigate the productivity channel within firms, and whether or not WFH agreements caused structural changes

[10]Commuting distance is computed as the distance in meters between to centroids of the municipality of residence and the municipality of work.

within plants.

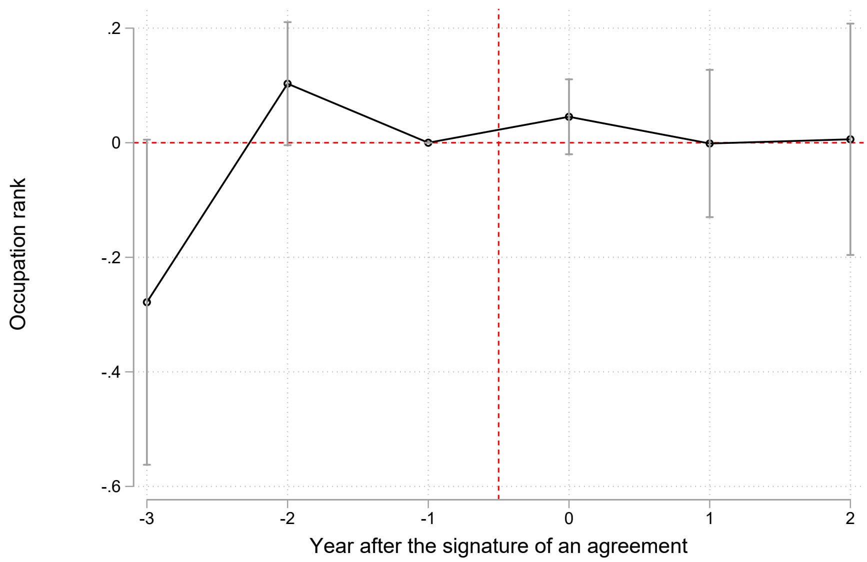
Figure 2: Event-study graph on hourly wage (log)



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on log hourly wage. Average log hourly wage one year before treatment: 3.2.

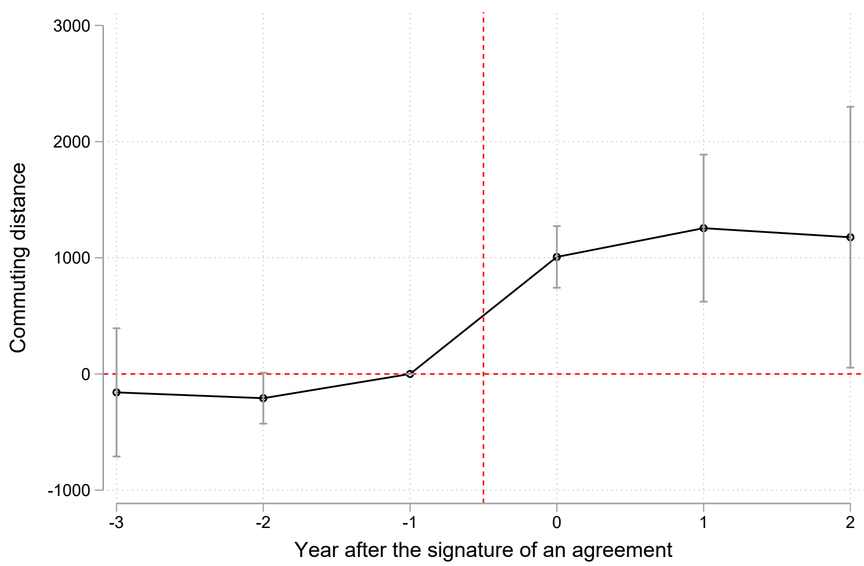
Robustness tests. We estimate a modified version of Equation 1 on a sample of treated and matched control individuals. We use a two-step matching procedure to build a control group of comparable workers who are working in plants that did not sign an agreement over the whole period. First, we match plants (without replacement) based on sector, plant size, share of female employees, share of permanent jobs, share of low-skilled employees and median hourly wage. We then pick individual controls inside these control plants, with replacement, based on a similar matching procedure on earnings, gender, age, an indicator for a permanent contract, working time, the urban area category of the municipality of residence, and the 2-digit occupation code, all measured in year 5 before the treatment. We end up with 183,607 individuals followed from 2009 to 2019, working in 1236 plants. Individuals are categorized as treated if they worked in a treated plant in all pre-event years, and as control if they worked in a control plant in all pre-event years, and matched to a treated worker. Figures A33 to A35 show results that confirm that the signature of agreements on working-from-home arrangements had positive effects on wages and commuting distance, and null effects on occupational rank.

Figure 3: Event-study graph on the occupation rank



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on the occupation rank. Average occupation rank one year before treatment: 22.4.

Figure 4: Event-study graph on commuting distance (meters)



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on commuting distance. Average commuting distance one year before the event: 41,444.8.

5 Mechanisms

There are three main mechanisms that can drive the effect of WFH arrangements on labor market outcomes. First, productivity could either increase, if working from home increases workers' well-being or allow them to be more focused. On the contrary, productivity could decrease if coordination costs are high or if workers are performing domestic tasks during their working hours. Second, WFH could relax the commuting constraint and give workers access to jobs associated with a higher wage or a higher rank in the occupational distribution. However, if WFH is an amenity merely substituting the low commuting time one, the effect on wages could be neutral. Finally, missing days at the workplace could threaten promotion perspective. In this section, we develop a heterogeneity analysis at the individual level that is guided by the exploration of the these three channels. Moreover, we explore the productivity channel by conducting an event-study analysis at the plant and firm level.

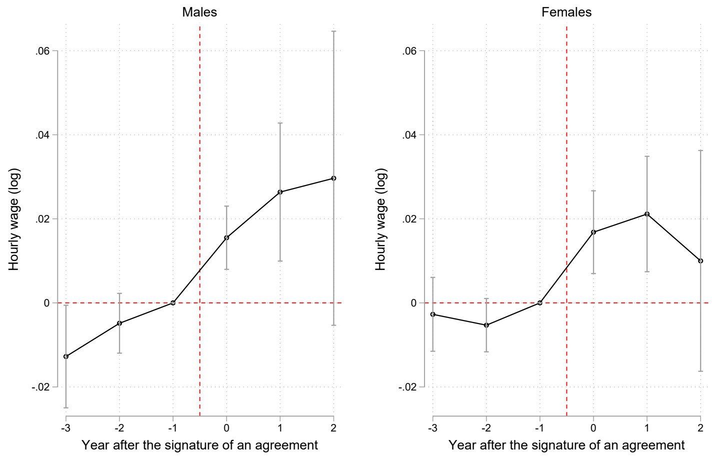
5.1 Individual-level analysis

We split the sample along three dimensions: (i) gender; (ii) individual WFH probability and (iii) whether workers move to a different plant. If a change in productivity drive the wage effects, we expect to find larger effects among workers with a higher individual probability to work from home. If the job search channel is at play, we expect workers moving to another plant to exhibit larger effects on their wage, occupational mobility and commuting distance, especially if the new plant has also adopted remote work. Female workers, who value WFH and low commuting time more than male workers on average, are also predicted to show larger effects. Finally, if WFH impacts promotions chances, we expect larger wage and occupational mobility effects on workers with a low probability to work from home. The expected direction of the effect according to each channel, and the implications in terms of heterogeneity, are summarized in Table A2 of Appendix A.

Effects by gender. We first examine whether our main results differ by gender. Figures 5 to 7 report the coefficients from Equation 1 estimated separately on each gender. Overall, we find quite similar labor market effects across male and female workers. However, we find that the effect on hourly wage seems to be slightly stronger and more persistent for men. Furthermore, Figures A9-A10 suggest that hourly wage gains for men are mostly explained by higher gross earnings, whereas for women hourly wage gains are due to a combination of an increase in gross earnings and a small decrease in working hours. Commuting distance is more markedly increasing for women, a finding that is compatible with the result established in the literature that the job search of women is more constrained by commuting time. The increase in commuting time for women is larger both in absolute and relative terms compared to men (about 1400 versus 1100 meters with a 4.2% versus

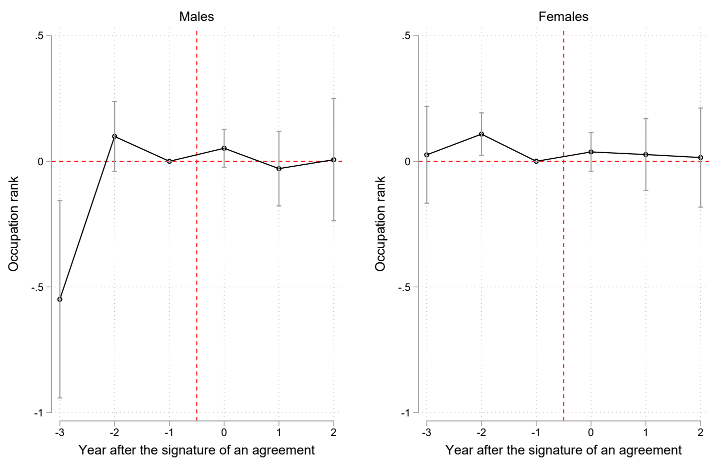
2.2% increase 1 year after the signature relative to one year before the signature). Taken together, these findings suggest that the option to work from home allowed all workers to extend the geographical scope of their search and seek jobs with higher pay, without necessarily changing occupation. In addition, it appears that the positive valuation of the WFH amenity does not fully neutralize the gains from releasing the commuting time constraint.

Figure 5: Event-study graph on hourly wage (log) by gender



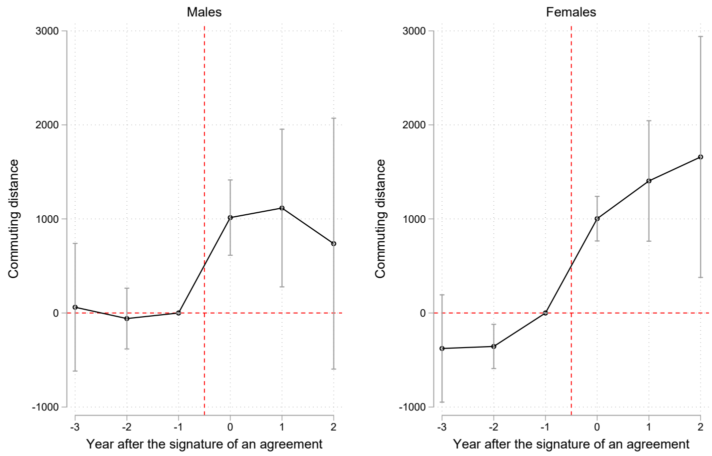
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on log hourly wage by gender. Average log hourly wage for males one year before treatment: 3.3. Average log hourly wage for females one year before treatment: 3.1.

Figure 6: Event-study graph on the occupation rank by gender



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on the occupation rank by gender. Average occupation rank for males one year before treatment: 23.2. Average for females one year before treatment: 21.5.

Figure 7: Event-study graph on commuting distance (meters) by gender



NOTE: this graph reports the β_j *coefficients from the estimation of Eq. 1 on commuting distance by gender. Average commuting distance for males one year before treatment: 49,015.4. Average outcome for females one year before treatment: 33,303.7.*

Effects by predicted working from home probability. We build a prediction model of the probability to work from home using a rich set of characteristics associated to workers and their jobs.[11] We train the model using a logistic regression on the Labor Force Survey data where we observe the remote work status. We use a binary outcome variable indicating whether the individual is a remote worker or not. Table A3 reports the output of the regression. We then perform an out-of-sample prediction for workers in our sample, using DADS data, and we split them at the median of the predicted probability to work from home (Figures A13-A15).[12]

Then, we interact the relative time dummies with a high WFH probability dummy in the event study regression. Workers above the median of the predicted probability are categorized as high WFH probability workers. Because we have individual variation in the probability to work from home, we can look at within-plant effects. The estimated equation writes as follows:

$$Y_{i,j,p,t} = \alpha_i + \sum_{\substack{j=-4 \\ j\neq -1}}^{2} \beta_j Dist_j \times High\_Pr(WFH)_i + \gamma_t + \delta_{p,t} + \epsilon_{i,j,p,t}, \quad (2)$$

where $\delta_{p,t}$ is the interaction of time and plant fixed effects, ensuring that we compare workers with different predicted WFH probabilities within treated plants.

[11]We use categorical variables for gender, whether the individual has a permanent contract or not, 5-year age group, occupation code (PCS) at the 2-digit level, 2-digit industry code (NAF), geographical location (region), urban area category. Additionally, we control for the level of gross income.

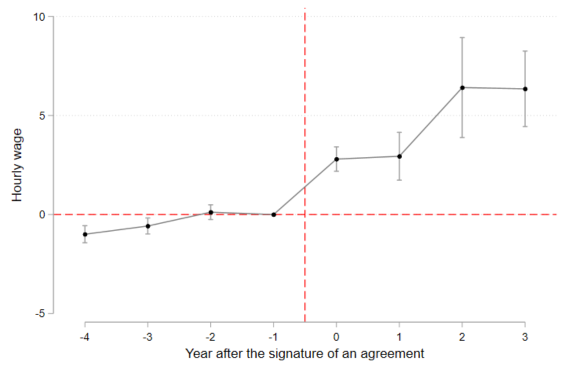
[12]Alternatively, we analyse the bottom and top quintiles of the predicted probability to work from home (A17-A19).

Figure 8 reports the β_j coefficients for three outcomes that are hourly wage, commuting distance and occupation rank. They show that within a treated plant, workers with the highest likelihood to work from home are experiencing larger wage gains, higher increase in commuting distance but a downward occupational mobility compared to workers in the same plant who are less likely to take up the WFH option. Figure A11 in Appendix A shows, however, contrasting results on hourly wage in logs. These two results taken together suggests that taking up the remote work option within a treated plant leads to absolute wage gains relative to coworkers less likely to work from home, but not necessarily to relative wage gains. However, results on occupation rank are consistent with the promotion channel suggesting that spending less time at the workplace relative to coworkers could influence managers' perceptions when deciding about promotions.

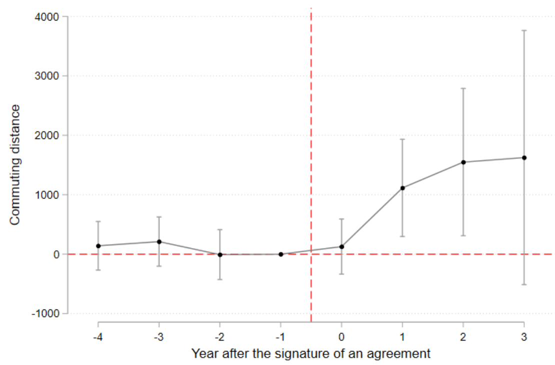
Beyond informing on the mechanisms, these within-plant findings also bring support to the idea that we measure the causal effect of working from home. The inclusion of plant fixed-effects allows to rule out alternative explanations such as any other simultaneous change at the plant level, or managerial practices that would differ between early and late treated plants.

Figure 8: Event-study estimates by WFH probability

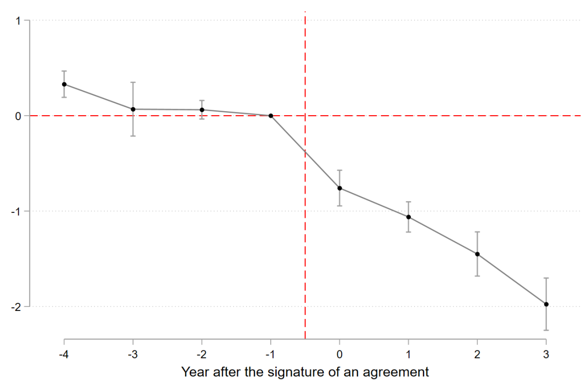
(a) Hourly wage (levels)



(b) Commuting distance (meters)



(c) Occupation rank

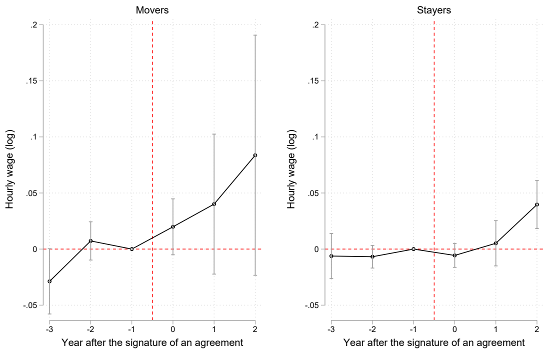


Notes: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 2. Average outcome one year before treatment: a) 30.4; b) 41279.4; c) 22.6.

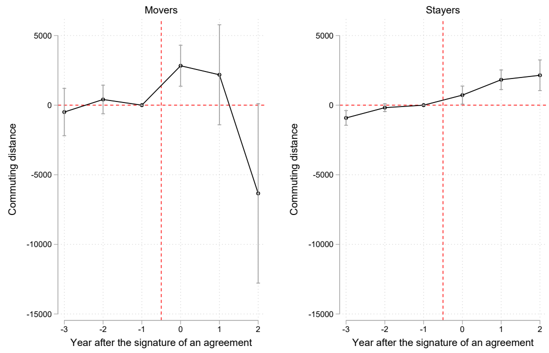
Effects by mover status. We split the sample between movers, i.e. workers who work at a different plant two years after the treatment, and stayers, i.e. workers who work at a the same plant two years after the treatment. Figure 9 shows that movers experience slightly larger wage effects, but similar increases in commuting distance, except for the negative effect in year two. One possible interpretation could be that some of the movers who changed jobs, and therefore experienced an increase in the commuting distance, have moved their residence afterwards, making the effect turn negative. At the same time, we also find an increase of about 2000 meters in the commuting distance of the "stayers" 2 years after treatment, which could signal that some "stayers" have taken the opportunity of remote work to change residence, therefore increasing their commuting distance. Occupation rank does not seem to respond to the signature of the WFH agreement for neither of the groups. In Figure 10, we further split the mover sample into those moving to a plant where a working-from-home agreement has been signed, i.e. where it is possible to work from home, and those moving to a non-treated plant. While wage effects are similar across groups, the increase in commuting distance is driven by workers moving to treated plant. In addition, workers moving to a treated plant are the only group for which we find an increase in occupation rank. It suggests that experiencing the possibility to work from home could have released some job search constraints and help them seek higher-paying jobs.

Figure 9: Event-study estimates by Movers vs. Stayers

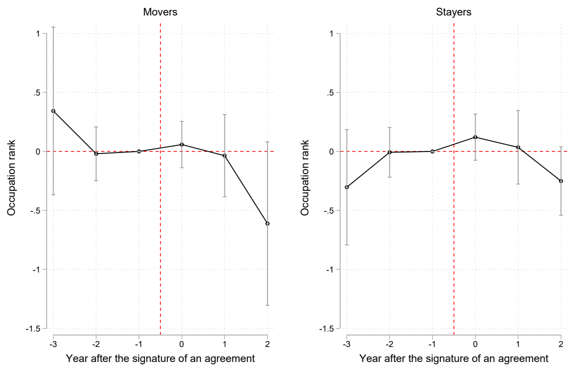
(a) Hourly wage (logs)



(b) Commuting distance (meters)



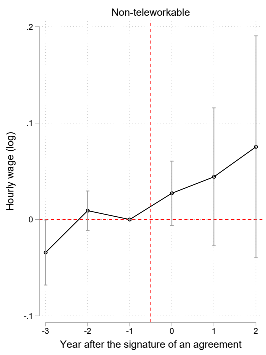
(c) Occupation rank



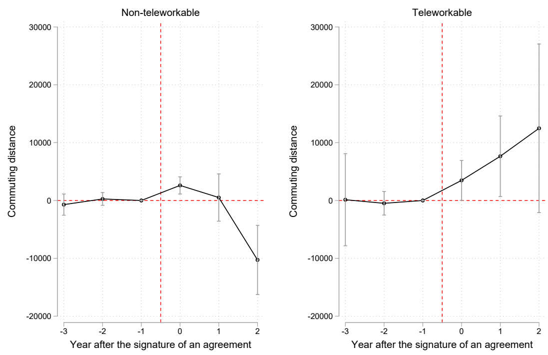
Notes: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 1. Average outcomes one year before treatment: a) average log hourly wage for movers: 3.2; average log hourly wage for stayers: 3.2; b) average commuting distance for movers: 65106.2; average commuting distance for stayers: 44922.3; c) Average occupation rank for movers: 23.6; average occupation rank for stayers: 21.9.

Figure 10: Event-study estimates by workers moving to non-teleworkable v. teleworkable plants

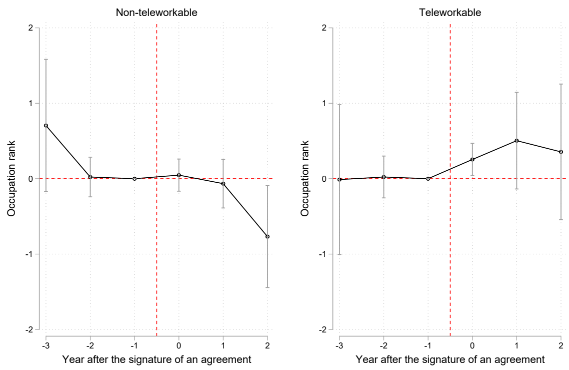
(a) Hourly wage (logs)



(b) Commuting distance (meters)



(c) Occupation rank



Notes: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 1. Average outcomes one year before treatment: a) average log hourly wage for movers to non-teleworkable plants: 3.2; average log hourly wage for movers to teleworkable plants: 3.2; b) average commuting distance movers to non-teleworkable plants: 66901.1; average commuting distance for movers to teleworkable plants: 57837.6; c) Average occupation rank movers to non-teleworkable plants: 23.6; average occupation rank for movers to teleworkable plants: 23.5.

Additional heterogeneity. To better understand the role of household responsibilities in influencing the relationship between WFH arrangements and labor market outcomes, we explore the heterogeneity of the results by whether workers have children or not. We rely on a subsample of private-sector workers that are matched to demographic information, and we split the sample between workers with no children and workers with children under 3 y.o. We chose to restrict to parents of small children since they might be the ones facing the greatest challenges to achieve a work-life balance. Figure A20 of Appendix A report the results. Since we are working on 4% of the private-sector employee population, and further splitting the sample, results are less precise. Still, we observe a positive impact of the signature of a WFH agreement for workers with no children on wages of about 2% one year after the signature. On the contrary, we detect a 2% negative impact on hourly wage for parents of young children.[13] These results suggest that childcare responsibilities are likely to mediate part of the effect of WFH on labor market trajectories. For workers with strong household responsibilities, the option to work from home seems to harm their wage growth.

Table 1 reports the coefficients from estimating the static version of Equation 1, where the event-time indicators are replaced with a single *Post* dummy across different subsamples. The results show that wage gains are concentrated among groups already performing relatively well in the labor market, i.e. white collar workers, permanent workers, workers in the top quartile of the wage distribution (although workers in the bottom quartile also display modest wage improvements). Table 1 also indicates that both male and female workers experience wage gains, although the increase in commuting distance is larger in absolute and relative terms for women, suggesting a decrease in the gender commuting gap. Comparing subgroups defined in terms of age and degree of urbanization of the municipality of residence, we additionally observe that positive effects are mainly observed for residents of large urban areas and workers in the top 25% of the age distribution. Interestingly, Table 1 also shows that wage gains are almost systematically associated with increases in commuting distance, supporting the job search channel.

[13] Further splitting by gender does not reveal a clear differentiated effect. Results are available upon request.

Table 1: Heterogeneity

	(1) Hourly Wage	(2) Commuting Distance
Non-white collars	1.0865***	375.5341*
	(0.30525)	(194.03780)
Observations	96591	96591
Outcome mean (pre event)	18.653	26314.585
White collars	3.1373***	1397.6406**
	(0.51443)	(299.66039)
Observations	209876	209876
Outcome mean (pre event)	32.018	45911.257
Fixed-term contract	-0.1326	74.5515
	(0.30762)	(1260.58493)
Observations	35603	35603
Outcome mean (pre event)	17.676	49185.714
Permanent contract	2.7192***	1357.6683***
	(0.42660)	(218.92599)
Observations	291927	291927
Outcome mean (pre event)	28.072	39114.755
Medium and small municipalities	1.1116	-940.5044**
	(0.95254)	(383.70740)
Observations	35009	35009
Outcome mean (pre event)	21.634	54315.398
Large cities	2.6781***	944.8774***
	(0.41145)	(218.38520)
Observations	280105	280105
Outcome mean (pre event)	28.326	37895.855
Males	3.3976***	1000.2970***
	(0.42303)	(293.39091)
Observations	160468	160468
Outcome mean (pre event)	31.000	48144.917
Females	1.6543***	1222.1162***
	(0.48834)	(264.19464)
Observations	146121	146121
Outcome mean (pre event)	24.011	30289.019
Q1 of Age distribution	0.6850***	470.3082
	(0.24491)	(522.70916)
Observations	118126	118126
Outcome mean (pre event)	21.744	39890.415
Q2 of Age distribution	1.2027***	552.9186*
	(0.28400)	(320.06595)
Observations	129462	129462
Outcome mean (pre event)	27.598	38938.176
Q3 of Age distribution	2.1080	1140.5384***
	(1.46753)	(278.53010)
Observations	123292	123292
Outcome mean (pre event)	30.472	39711.789
Q4 of Age distribution	6.3506***	1986.6524***
	(0.45678)	(291.67927)
Observations	101169	101169
Outcome mean (pre event)	33.140	39258.651
Q1 of wage distribution	0.3074**	-133.4397
	(0.11760)	(385.42314)
Observations	135805	135805
Outcome mean (pre event)	15.573	33432.794
Q2 of wage distribution	0.0409	568.1939***
	(0.11760)	(173.11149)
Observations	138179	138179
Outcome mean (pre event)	20.425	29566.271
Q3 of wage distribution	-0.4654	699.3271***
	(0.47982)	(243.53837)
Observations	131839	131839
Outcome mean (pre event)	27.651	40136.873
Q4 of wage distribution	7.1917***	1779.0575***
	(1.31255)	(394.53508)
Observations	105693	105693
Outcome mean (pre event)	50.125	57492.348

5.2 Plant and Firm-level Analysis

Working-from-home arrangements could cause structural changes within plants and firms, and have an impact on their productivity through an increase in revenues, a reduction of costs, or a combination of these two. In this section, we investigate this by conducting an analysis both at the plant and firm level. We explore the effects of signing a WFH agreement on the organizational structure of the plants. Then, we investigate the drivers of the productivity effect at the firm level by focusing on those firms that had at least one plant signing a teleworking agreement. We therefore estimate Equation 1 where the unit of observation is either the plant or the firm. The sample of plants and firms include all workers, both incumbent and newly hired ones.

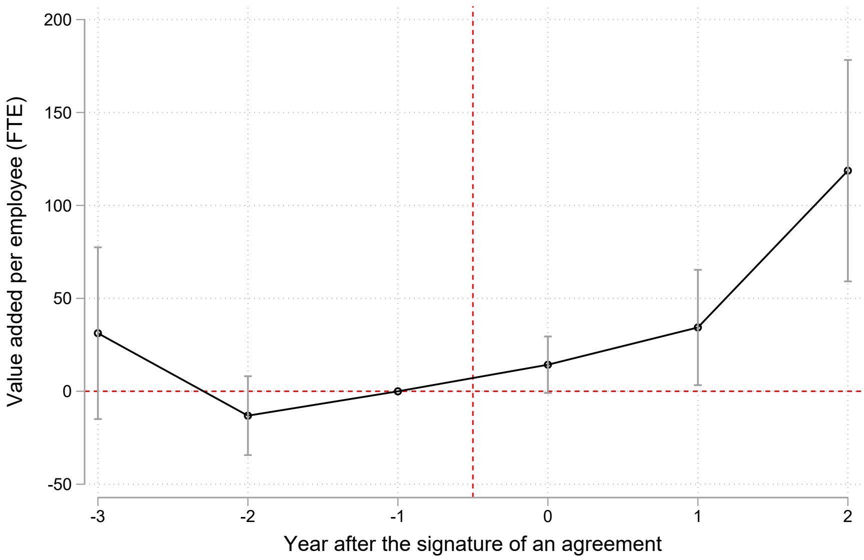
Plant-level analysis. We test several outcomes to investigate whether the productivity effects of working-from-home arrangements can be explained by organizational changes at the plant level. Overall, we do not find evidence that this is the case. After the signature, no significant change is observed for the size of the plant, expressed in terms of the number of workers employed (figure A22), shares of different categories of workers (figure A23), share of female workers (figure A24), share of permanent contracts (figure A25).

Firm-level analysis. Figure 11 shows that value added normalised by the number of employees in full time equivalent gradually increases after the signature of a WFH agreement in at least one plant of the firm.[14] On the revenue side, we observe that the increase of the value of production per FTE employee is mainly driven by a larger provision of services (see figure A26), whereas the change in the value of goods sold is slight and non statistically significant at the 5% level. Then, we find that firms' operating costs, normalized by the number of employees in FTE, also increase.[15] This is partly explained by a higher salary costs per employee in FTE (figure A27), meaning that firms with at least one plant-level WFH agreement offer higher wages to their workers on average. The size of the firms does not change significantly, as the number of employees expressed in full time equivalent remains roughly stable (figure A28). Finally, while we find evidence that the stock of some types of asset increases relative to the number of employees (e.g. tangible and financial assets), the effects are not statically significant (figure A29).

[14]Value added is defined as the value of output minus the value of intermediate inputs.

[15]Notice that operating costs include but are not limited to intermediate costs. Operating costs include also other costs related to recurring and day-to-day expenses that are necessary to run the firm's activity, e.g. rent costs, salary costs.

Figure 11: Event-study graph on value added per employee in full time equivalent.



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on value added per employee in full time equivalent. Average outcome one year before treatment: 152.7.

5.3 Discussion

Overall, the heterogeneity analysis at the individual level coupled with the plant and firm-level analyses suggest that the productivity and job search channels are the most salient mechanisms.[16]

The increase in value added per full-time-equivalent worker can be driven by either better matches of incoming workers or by an improvement in the productivity of incumbent workers. To disentangle between both channels, we examine outcomes of new hires. Figures A30 and A32 show a large increase both in hourly wages and commuting distance, supporting the hypothesis that both workers and employers are able to expand the geographical scope of their search for jobs or workers, leading to better matches.[17] This is also in line with recent evidence on the post-Covid period in France that shows that the pandemic-induced shift to remote work led to increases in commuting distance driven by firms hiring more distant and more productive workers (Boeri and Rigo, 2025). These results confirm that the option to work from home led to productivity gains at the firm level, partly driven by the recruitment of more productive workers.

[16]Note that the heterogeneous results found in Section 5 could also be driven by differences in take-up. However, Figures A3 to A5 show that, for all subgroups represented, and except for blue-collar workers, we observe a significant increase in take-up. It suggests that at least part of the heterogeneity we measure comes from differences in response to remote work rather than differences in take-up.

[17]We cannot exclude, though, that treated plants offer higher wages to incumbent workers even if they are not more productive.

6 Conclusion

The shift to remote work has been one of the largest transformations of modern labor markets, with roots going back to before Covid-19. Understanding its medium-run consequences is therefore essential for assessing how work arrangements shape workers' careers and firms' productivity. In this paper, we exploit quasi-experimental variation in access to remote work generated by the staggered adoption of plant-level teleworking agreements in France between 2014 and 2017. Using an event-study design and rich administrative data, we document the effects of remote work arrangements on wages, occupational mobility, commuting distance, and productivity.

Our main findings can be summarized as follows. First, access to remote work leads to modest but statistically significant wage gains, on the order of 2–3 percent within two years of adoption. These wage gains do not come with changes in the occupational ladder on average, but are accompanied by higher commuting distances, suggesting that remote work relaxes job search constraints and allows workers to access better-paying jobs. Second, we find evidence of productivity gains at the firm level, measured by increases in value added per full-time-equivalent worker. These gains appear to be driven both by improvements in the productivity of incumbent workers and by the recruitment of more productive workers from a broader geographical pool. Third, while remote work is often viewed as a job amenity, our results indicate that its effects are not limited to amenity substitution. Wage gains are larger for workers who change plants after the adoption of a remote work agreement, especially for those moving to teleworkable plants, pointing to an expansion of job search opportunities rather than a pure compensating differential mechanism. Then, we also explore heterogeneity across workers, with a particular focus on gender and household constraints. We find broadly similar wage and mobility effects for men and women. However, women experience a larger increase in commuting distance following the adoption of remote work arrangements, consistent with existing evidence that commuting constraints are more binding for women. Despite this relaxation of commuting constraints, we do not find substantially larger wage gains for women overall, suggesting that the positive valuation of remote work as an amenity may partly offset the benefits from expanded job opportunities.

From a policy perspective, these findings suggest that remote work arrangements can generate efficiency gains for both workers and firms, but that their distributional effects depend on workers' ability to convert flexibility into improved job matches. While remote work may help relax commuting constraints, especially for women, it does not by itself eliminate the barriers associated with household responsibilities.

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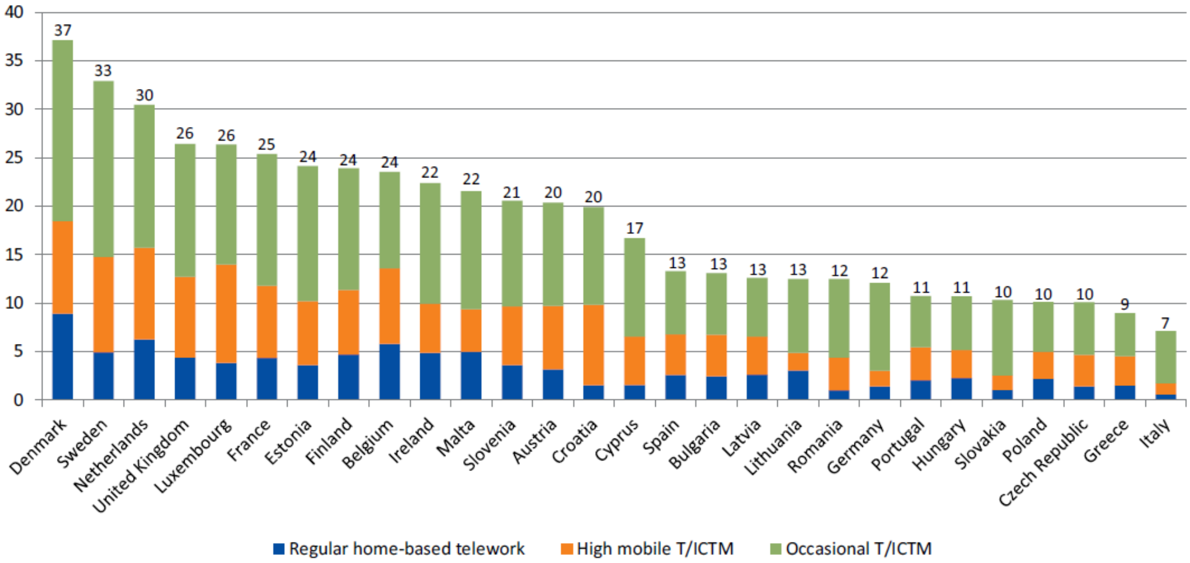
A Appendix: Additional Tables and Figures

Figure A1: Percentage of employees doing T/ICTM in the EU28, by category and country (EWCS 2015)



Source: EWCS 2015 (Messenger, 2018)

Table A1: Descriptive statistics on workers in treated plant by year of signature.

	Treated in 2014	Treated in 2015	Treated in 2016	Treated in 2017
Female	0.411	0.468	0.465	0.499
Age	44.382	43.911	44.089	44.366
Annual earnings	60886.933	60720.715	50434.382	48419.086
Working time	0.898	0.890	0.883	0.898
Employment spell duration	346.271	347.046	333.773	345.359
Average % change in earnings in the 5 past years	1.620	1.132	0.340	0.285
Cities in a large urban hub	0.710	0.793	0.674	0.674
Cities in the periphery of a large urban hub	0.231	0.164	0.210	0.241
Multi-polar cities in large urban areas	0.031	0.025	0.048	0.037
Other multi-polar cities	0.011	0.007	0.028	0.018
White collars	0.489	0.534	0.379	0.402
Intermediate professions	0.264	0.214	0.263	0.276
Clerical workers	0.132	0.170	0.185	0.179
Blue-collar workers	0.114	0.080	0.171	0.139
Observations	27544	32174	18366	37683

Table A2: Summary of the main potential channels

Channel	Mechanisms	Predictions	Empirical findings
Productivity	(+) Increased well-being, improved concentration	Larger positive effects for workers more likely to work from home	Larger wage effects for male workers, workers without children and workers with a larger probability to work from home
	(−) Coordination costs, disruption of domestic tasks	Larger negative effects for workers with children and for women	
Promotions	(−) Fewer in-person interactions with managers	Larger negative effects for workers more likely to work from home	Larger positive effects on commuting distance for workers more likely to work from home
	(−) Lower visibility and information about promotion opportunities		Larger positive effects on the probability of being promoted for workers less likely to work from home
Job search	(+) Expansion of the scope of job search	Larger effects for workers with high valuation of WFH / low commuting time (e.g. women)	Larger positive effects on commuting distance for women
	(0) WFH substitutes for the low-commuting-time amenity	Larger effects for workers moving to a new plant	Larger positive effects on commuting distance for workers moving to a teleworkable plant

Table A3: Prediction output from logistic regression of worker's remote status.

	(1) WFH prediction
Remote	
Permanent contract	-0.0183
	(0.152)
Female	-0.155**
	(0.0728)
PCS=21	3.130***
	(1.091)
PCS=22	3.167***
	(1.003)
PCS=23	2.461**
	(1.003)
PCS=31	2.782***
	(0.823)
PCS=33	2.872***
	(0.735)
PCS=34	3.172***
	(0.737)
PCS=35	2.805***
	(0.776)
PCS=36	5.165***
	(1.580)
PCS=37	3.533***
	(0.727)
PCS=38	3.254***
	(0.727)
PCS=42	2.045***
	(0.744)
PCS=43	1.789**
	(0.742)
PCS=45	1.838**
	(0.748)
PCS=46	2.666***
	(0.727)
PCS=47	1.674**
	(0.735)
PCS=48	1.426*
	(0.761)
PCS=52	0.342
	(0.754)
PCS=53	0.339
	(0.857)
PCS=54	2.019***
	(0.735)
PCS=55	0.606
	(0.801)
PCS=56	0.795
	(0.813)
PCS=62	-1.019
	(0.925)
PCS=64	-0.410
	(1.018)
PCS=65	-0.502
	(1.013)
Gross earnings	0.00000750***
	(0.00000175)
Constant	-3.503*
	(1.817)
Observations	15257
Pseudo R^2	0.243

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A2: Share of different types of workers by quintile of predicted WFH probability.

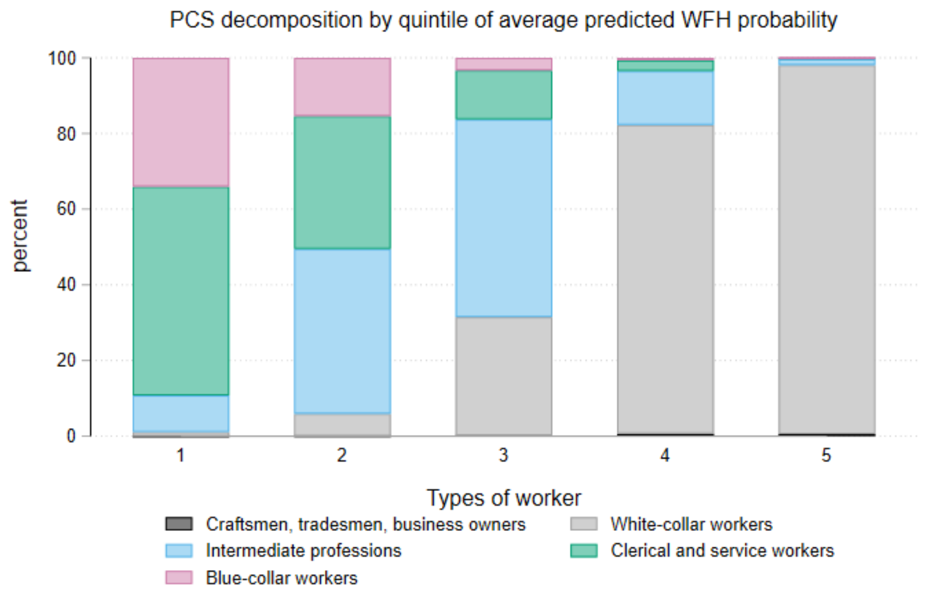
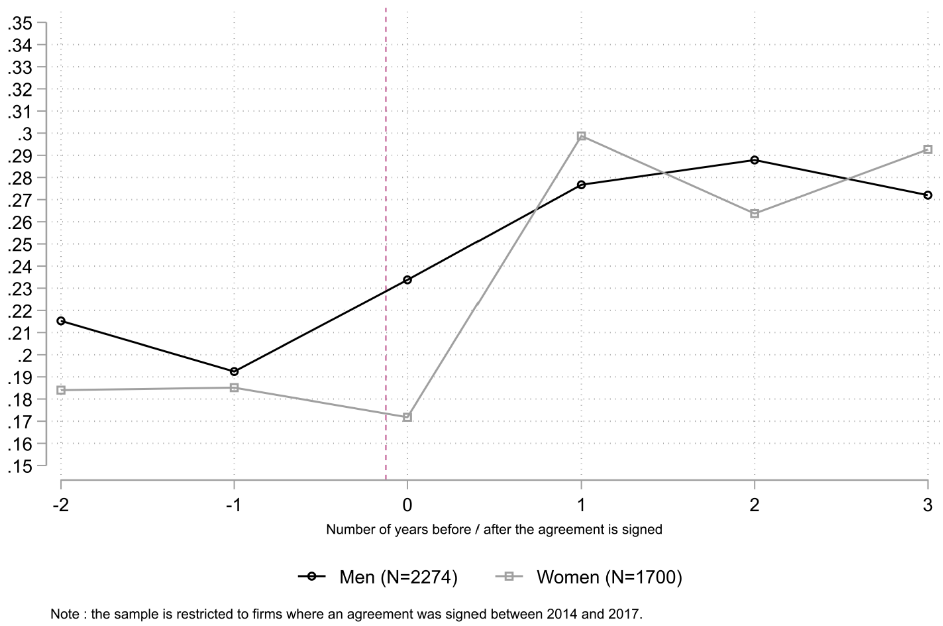
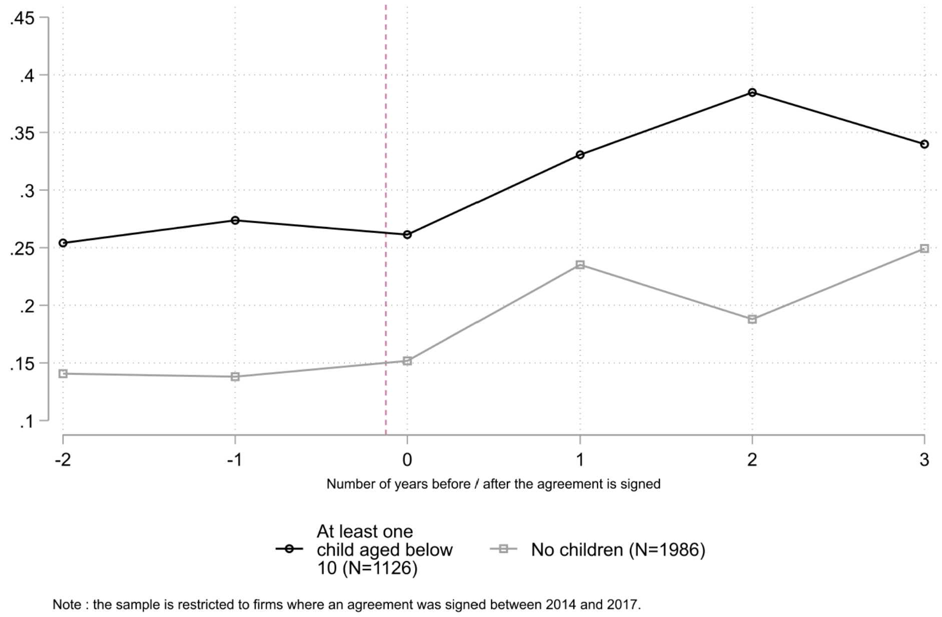


Figure A3: Share of workers WFH in the last 4 weeks - by gender



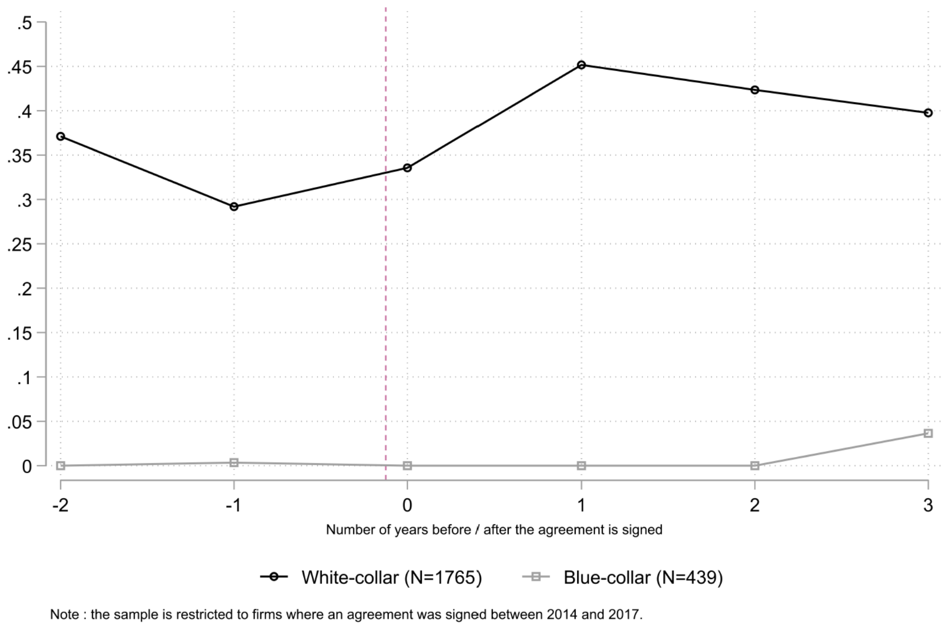
NOTE: This graph plots separately by gender the share of employees reporting having worked from home in the last 4 years in plants that signed a WFH agreement between 2014 and 2017.

Figure A4: Share of workers WFH in the last 4 weeks - by number of children



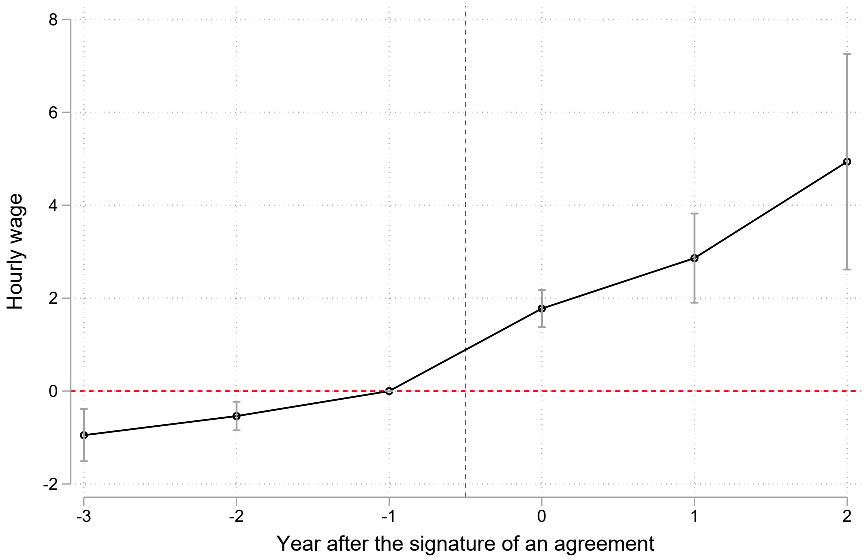
NOTE: This graph plots separately by number of children the share of employees reporting having worked from home in the last 4 years in plants that signed a WFH agreement between 2014 and 2017.

Figure A5: Share of workers WFH in the last 4 weeks - white-collar versus blue-collar



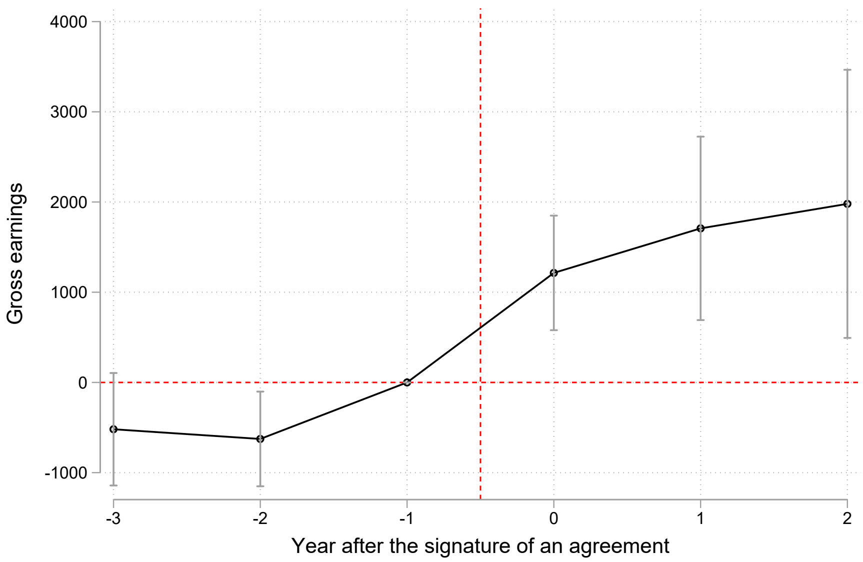
NOTE: This graph plots separately for white vs. blue-collar workers the share of employees reporting having worked from home in the last 4 years in plants that signed a WFH agreement between 2014 and 2017.

Figure A6: Event-study graph on hourly wage expressed in levels



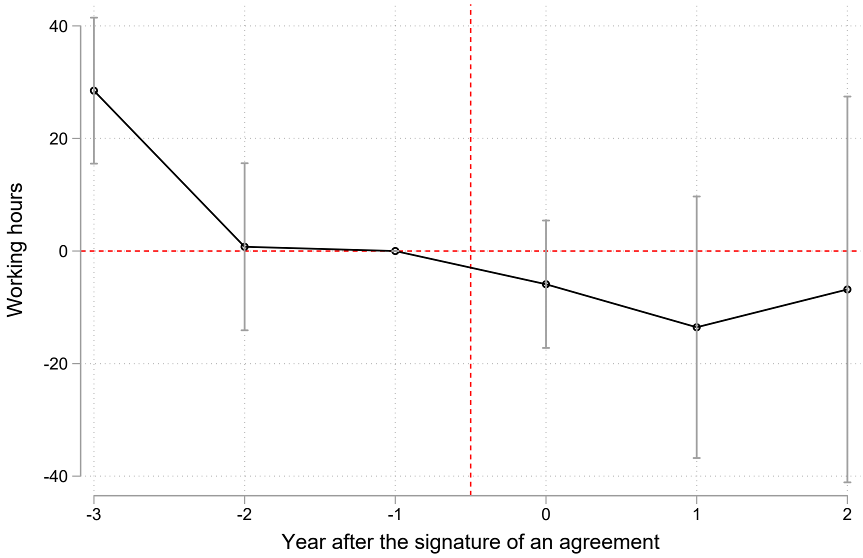
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on hourly wage expressed in levels. Average outcome one year before the event: 30.3.

Figure A7: Event-study graph on gross earnings



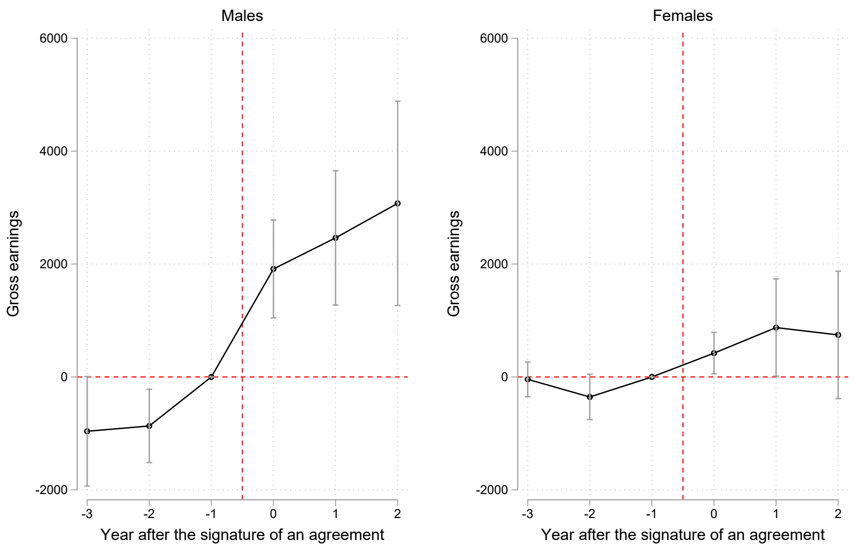
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on gross earnings. Average gross earnings one year before treatment: 52,938.6.

Figure A8: Event-study graph on working hours



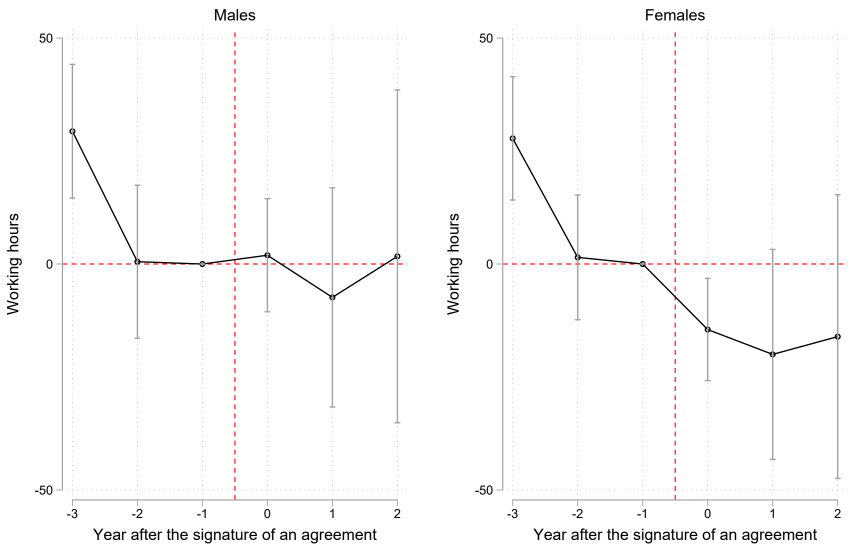
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on working hours. Average amount of working hours one year before treatment: 1719.

Figure A9: Event-study graph on gross earnings by gender



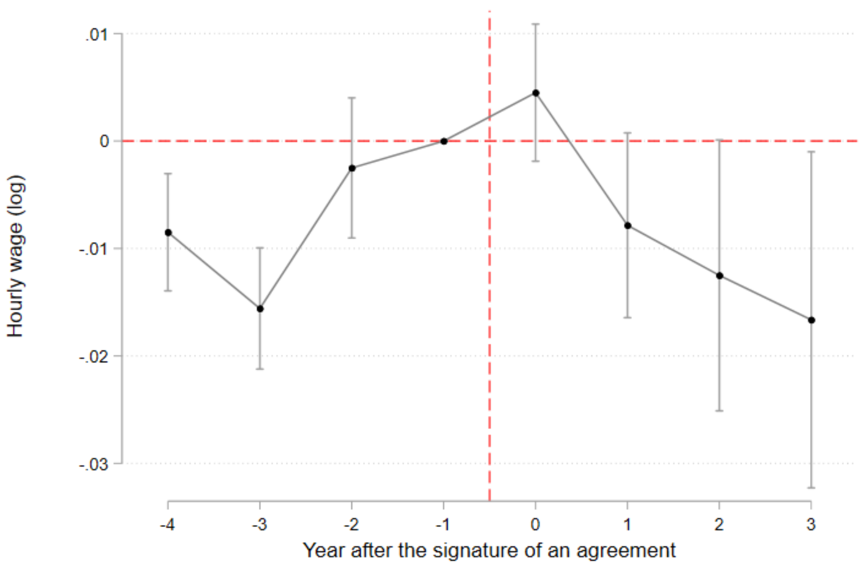
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on gross earnings by gender. Average gross earnings one year before treatment for men: 61,211.1. Average gross earnings one year before treatment for women: 43,853.7.

Figure A10: Event-study graph on working hours by gender



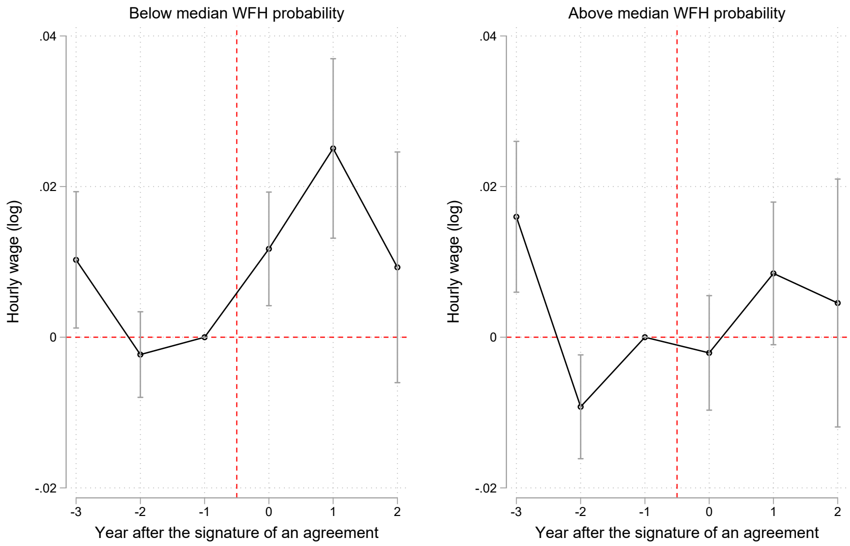
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on working hours by gender. Average number of working hours one year before treatment for men: 1769. Average number of working hours one year before treatment for women: 1664.

Figure A11: Event-study graph on hourly wage (log) by predicted WFH probability



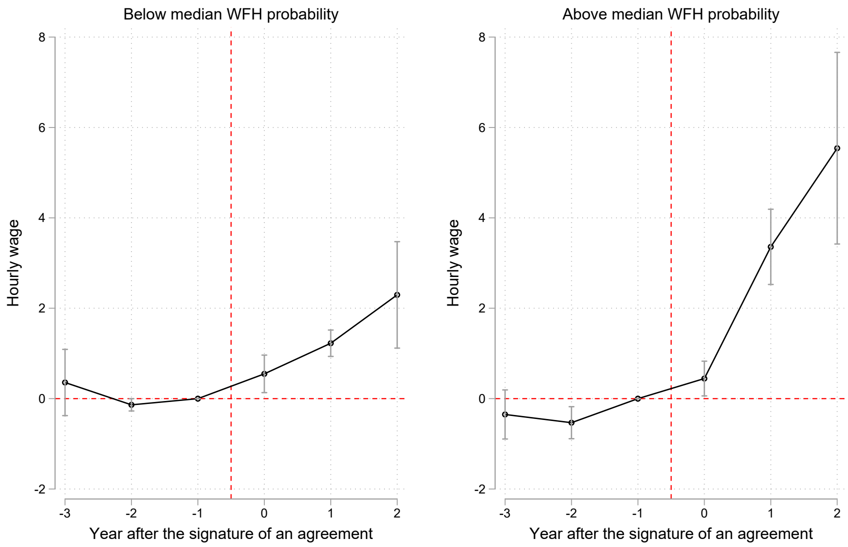
NOTE: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 2.

Figure A12: Event-study graph on hourly wage (log) below and above the median of predicted WFH probability



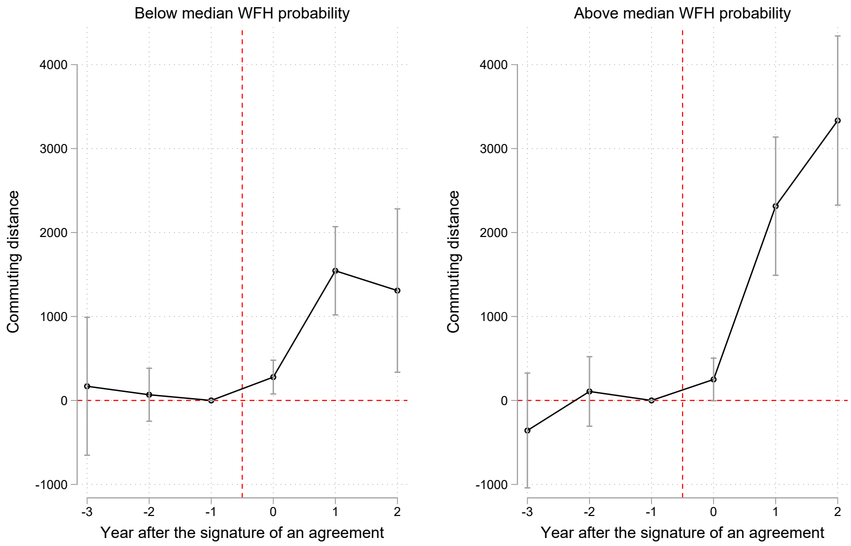
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 below and above the median predicted WFH probability. Average outcome one year before treatment: a) below median predicted WFH probability: 2.9; b) above median predicted WFH probability: 3.5.

Figure A13: Event-study graph on hourly wage below and above the median of predicted WFH probability



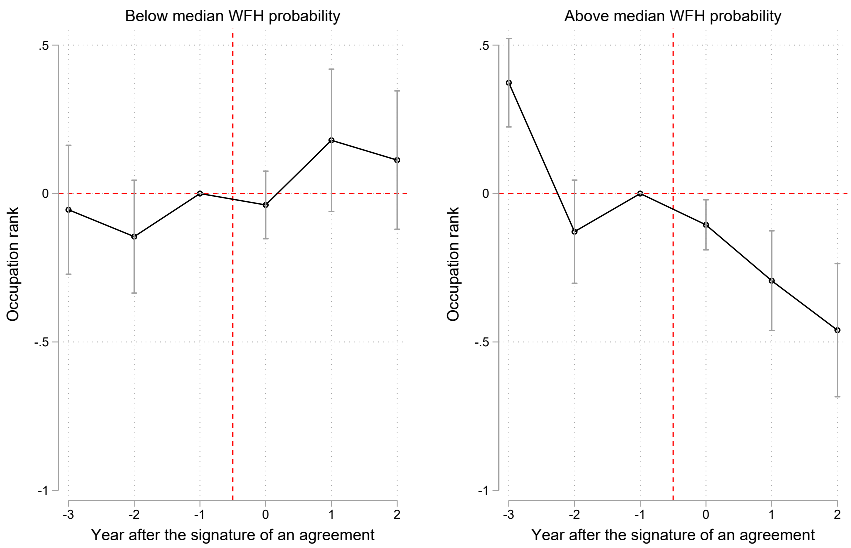
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 below and above the median predicted WFH probability. Average outcome one year before treatment: a) below median predicted WFH probability: 20.1; b) above median predicted WFH probability: 39.7.

Figure A14: Event-study graph on commuting distance below and above the median of predicted WFH probability



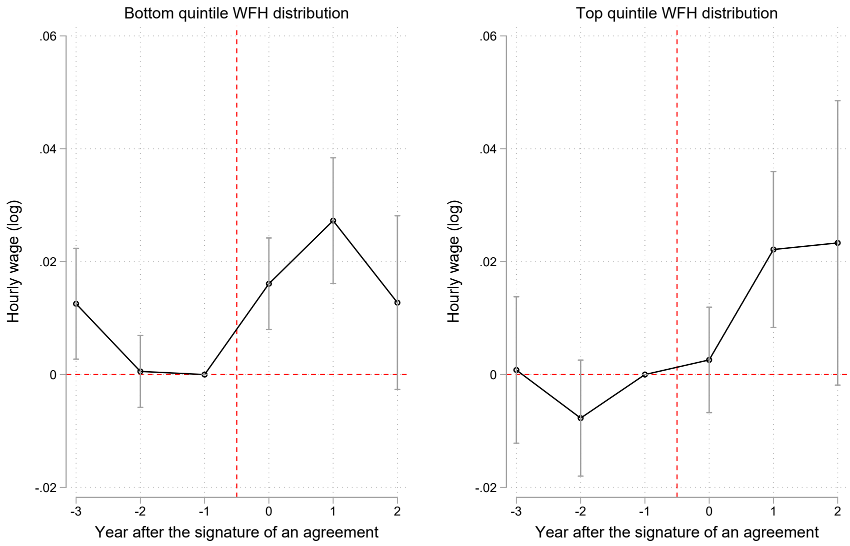
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 below and above the median predicted WFH probability. Average outcome one year before treatment: a) below median predicted WFH probability: 31536.5; b) above median predicted WFH probability: 50136.9.

Figure A15: Event-study graph on occupation rank below and above the median of predicted WFH probability



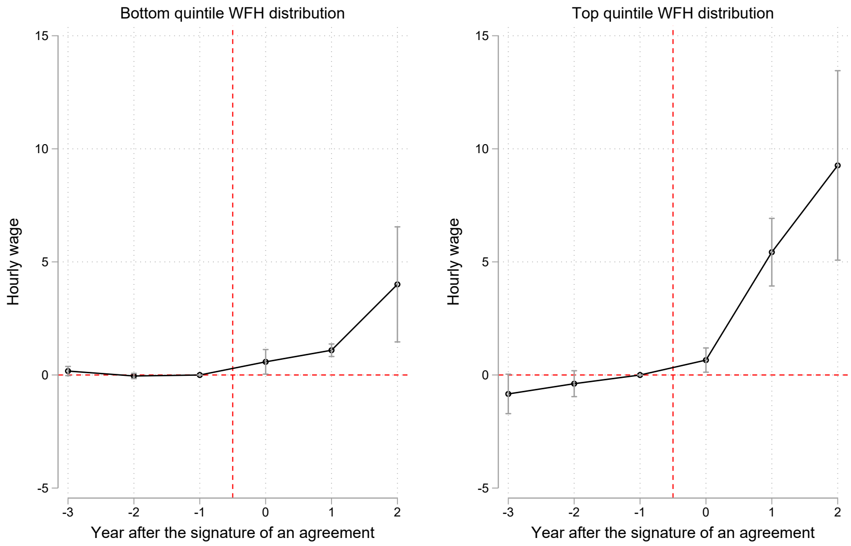
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 below and above the median predicted WFH probability. Average outcome for individuals one year before treatment: a) below median predicted WFH probability: 16.9; b) above median predicted WFH probability: 27.8.

Figure A16: Event-study graph on hourly wage (log) for the bottom and top quintiles of predicted WFH probability



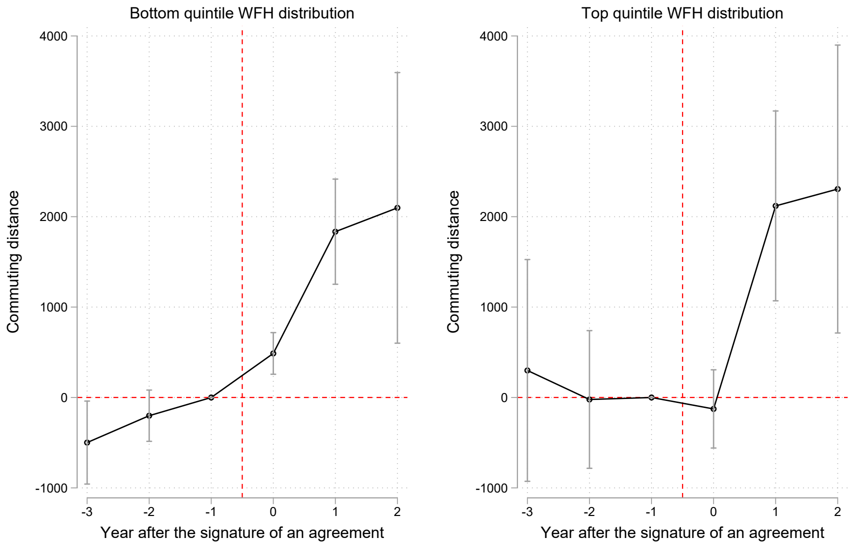
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 for the bottom and top quintiles of the predicted WFH probability. Average outcome one year before treatment: a) bottom quintile predicted WFH probability: 2.8; b) top quintile predicted WFH probability: 3.7.

Figure A17: Event-study graph on hourly wage for the bottom and top quintiles of predicted WFH probability



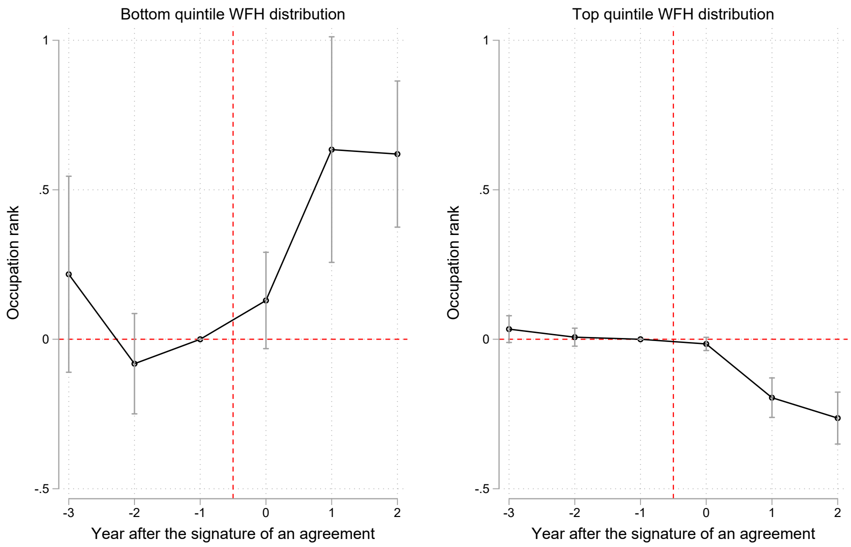
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 for the bottom and top quintiles of the predicted WFH probability. Average outcome one year before treatment: a) bottom quintile predicted WFH probability: 17,7; b) top quintile predicted WFH probability: 49.0.

Figure A18: Event-study graph on commuting distance for the bottom and top quintiles of predicted WFH probability



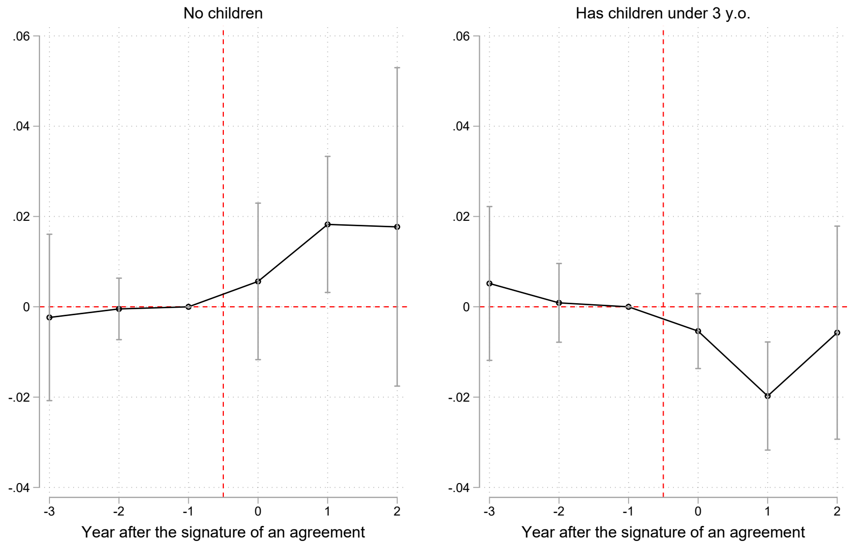
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 for the bottom and top quintiles of the predicted WFH probability. Average outcome one year before treatment: a) bottom quintile predicted WFH probability: 24011,1; b) top quintile predicted WFH probability: 54018.0.

Figure A19: Event-study graph on occupational mobility for the bottom and top quintiles of predicted WFH probability



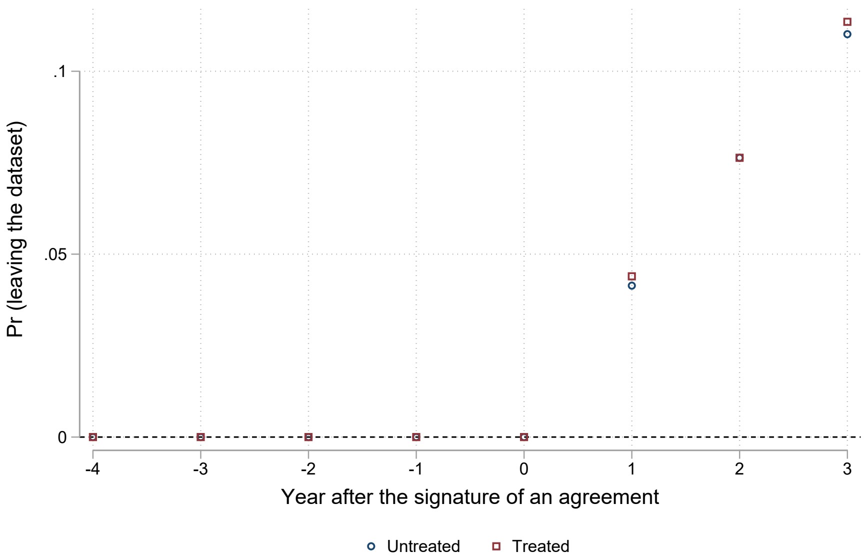
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 for the bottom and top quintiles of the predicted WFH probability. Average outcome one year before treatment: a) bottom quintile predicted WFH probability: 13.5; b) top quintile predicted WFH probability: 29.7.

Figure A20: Event-study graph on hourly wage (log) by number of children



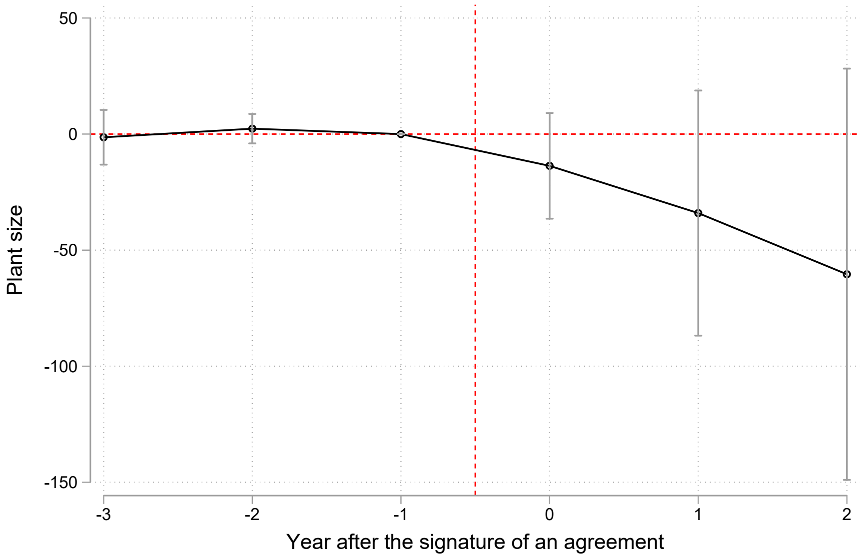
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on log hourly wage. Average outcome with no children one year before treatment: 3.2 . Average commuting distance for individuals with children one year before treatment: 3.2.

Figure A21: Probability of leaving the dataset by treatment status



NOTE: this graph reports the probability of leaving the non exhaustive dataset (12th sample) for treated individuals versus controls.

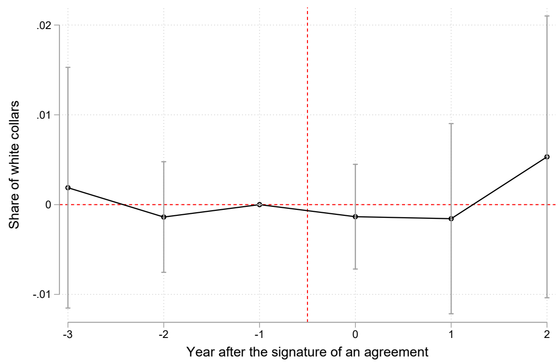
Figure A22: Event-study graph on plant size (number of effective employees in full time equivalent).



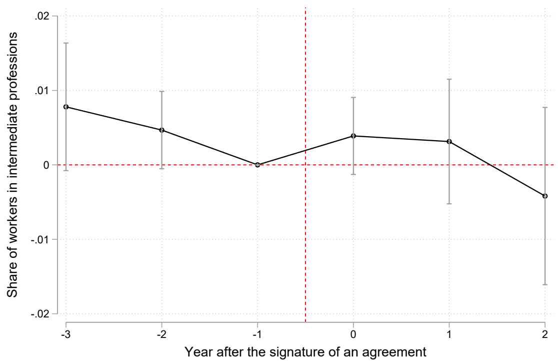
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on plants. Average outcome one year before treatment: 302.3.

Figure A23: Event-study estimates on the share of different types of worker at the plant level.

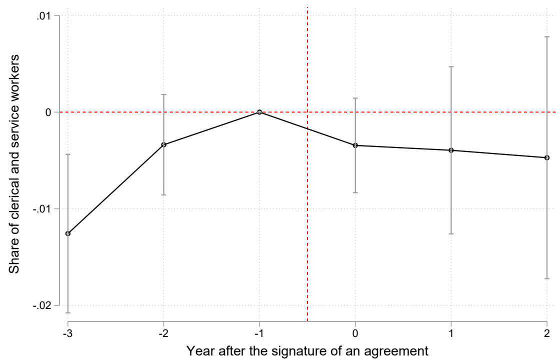
(a) White-collar workers



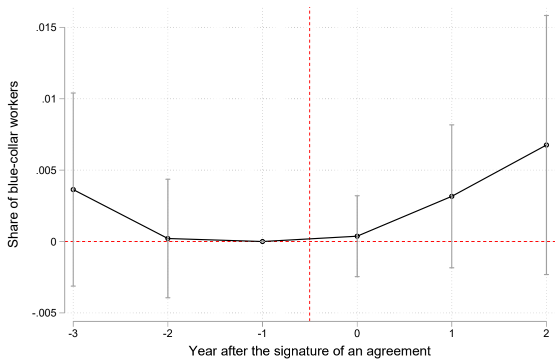
(b) Intermediate professions



(c) Clerical and service workers

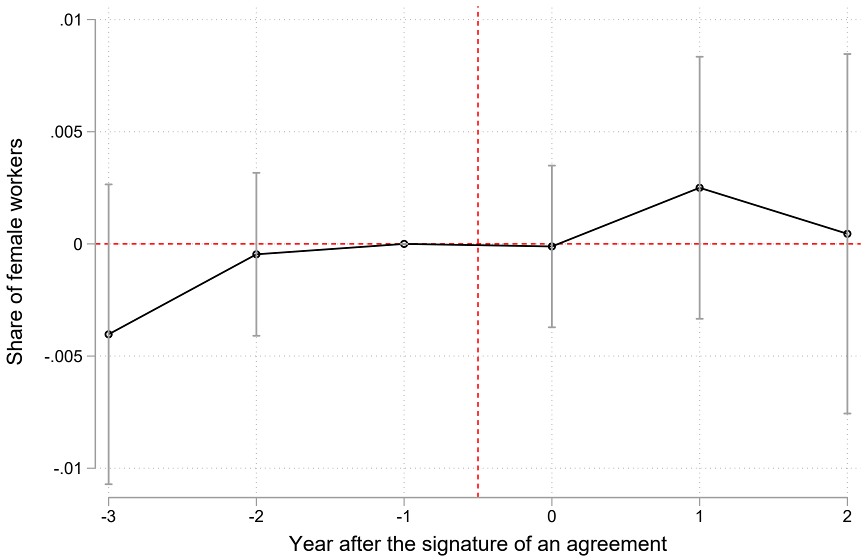


(d) Blue-collar workers



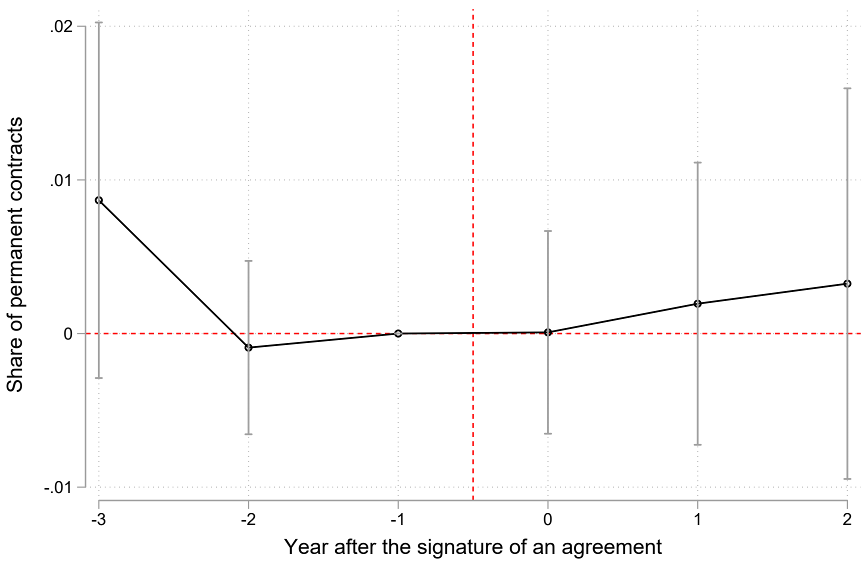
Notes: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 1 on plants. Average outcome one year before treatment: a)0.455; b) 0.233; c) 0.223; d) 0.078.

Figure A24: Event-study graph on the share of female workers at the plant level.



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on plants. Average outcome one year before treatment: 0.497.

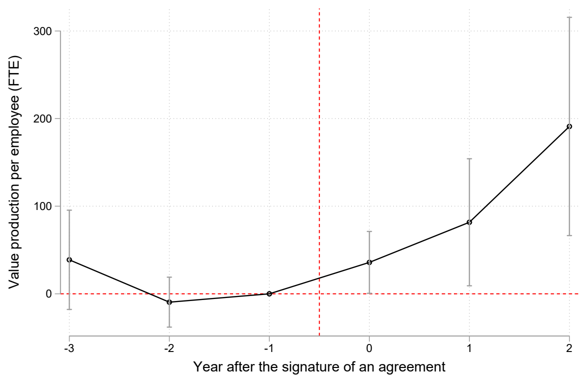
Figure A25: Event-study graph on the share of workers with permanent contracts at the plant level.



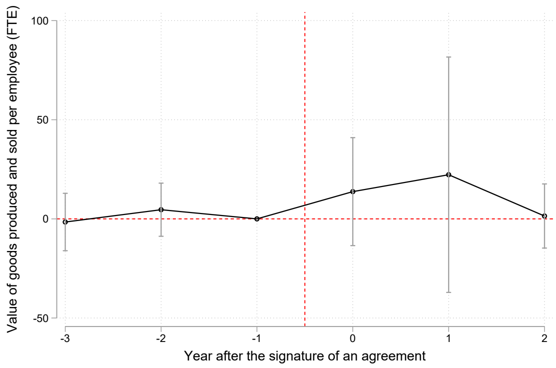
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on plants. Average outcome one year before treatment: 0.829.

Figure A26: Event-study estimates on the value of total production, production of goods, and services per employee in full time equivalent (FTE).

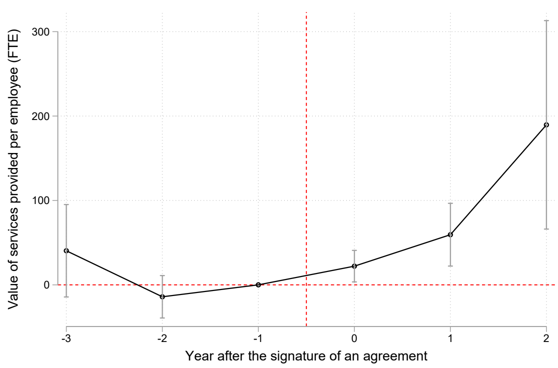
(a) Value of Production



(b) Goods



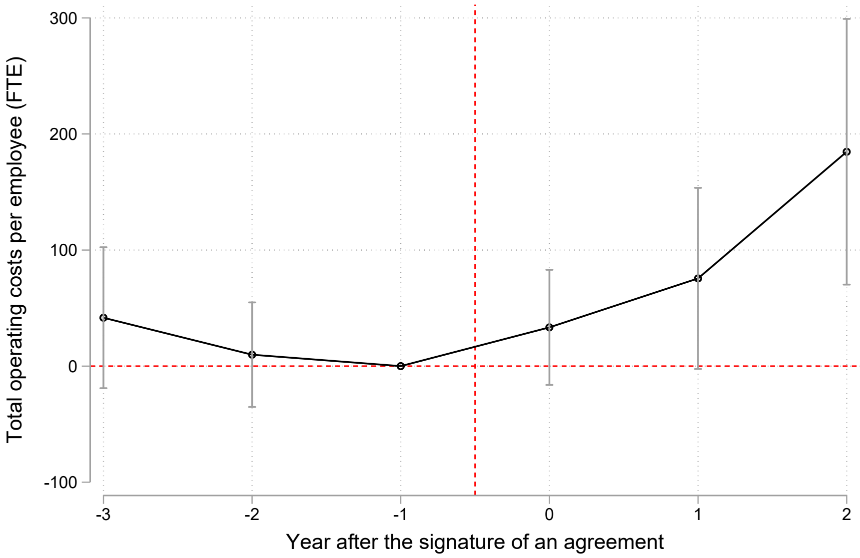
(c) Services



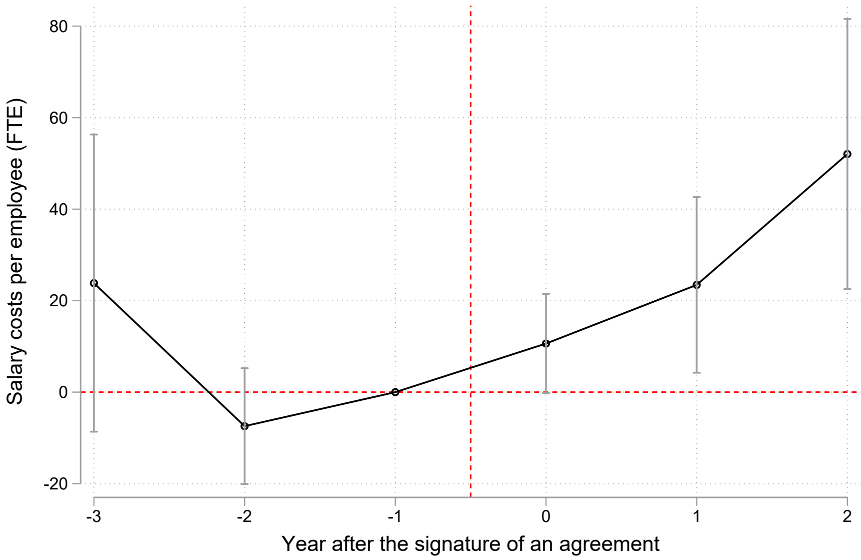
Notes: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 1 on firms. Average outcome one year before treatment: a); 300.2 b); 69.6 c) 230.6.

Figure A27: Event-study estimates on operating and salary costs per employee in full time equivalent (FTE).

(a) Operating Costs

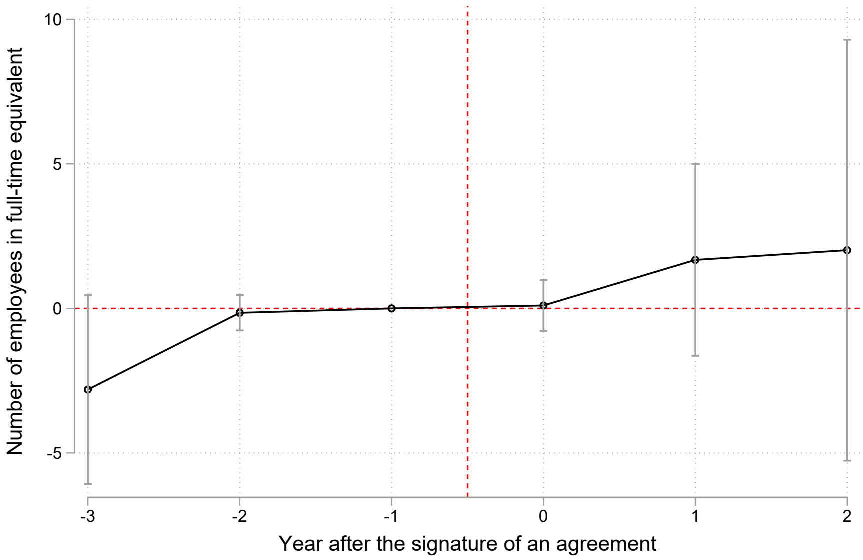


(b) Salary Costs



Notes: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 1 on firms. Average outcome one year before treatment: a) 503.3; b) 96.1.

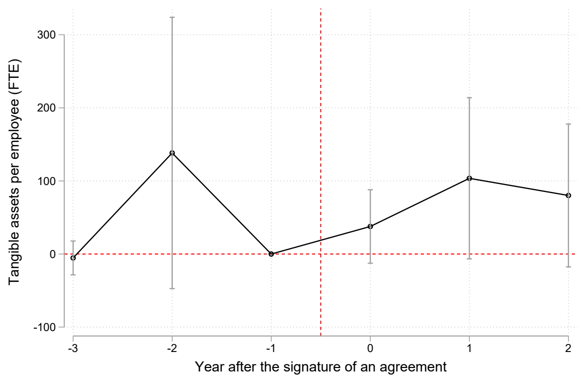
Figure A28: Event-study graph on number of employees in full time equivalent.



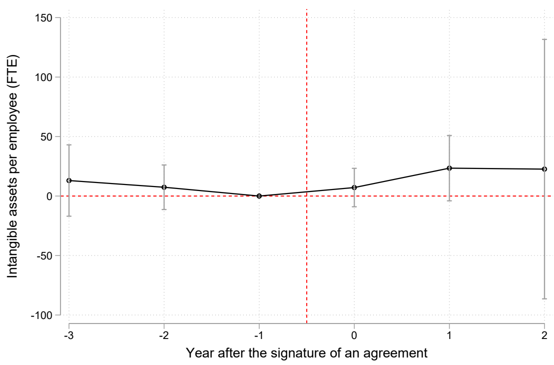
NOTE: this graph reports the β_j *coefficients from the estimation of Eq. 1 on firms. Average one year before treatment: 95.2.*

Figure A29: Event-study estimates on the value of different types of assets, normalised by the number of employees in full time equivalent (FTE).

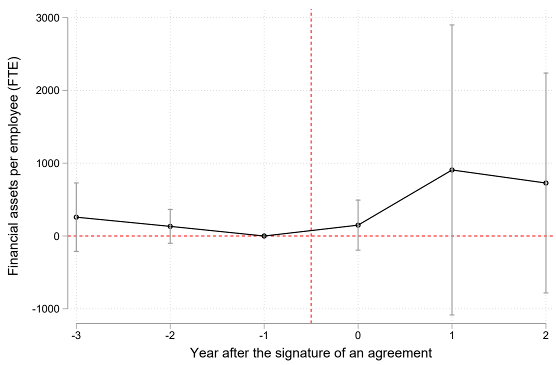
(a) Tangible Assets



(b) Non-tangible Assets

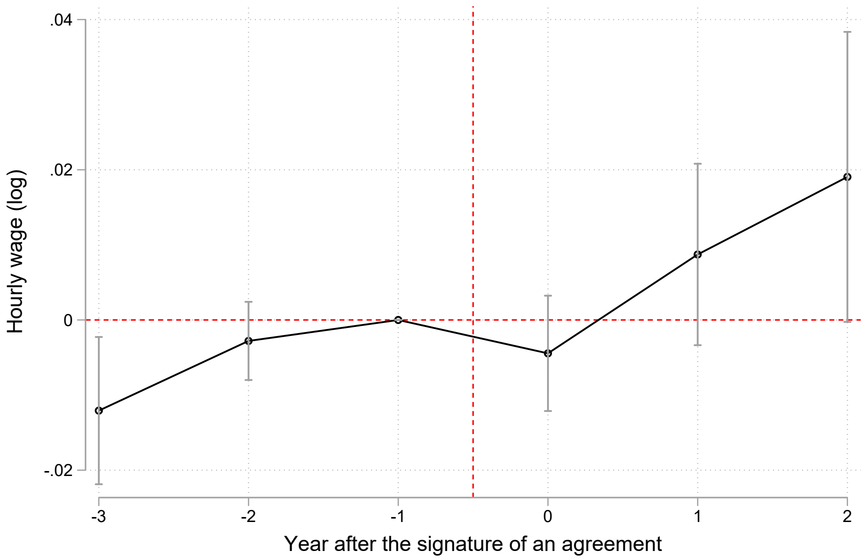


(c) Financial Assets



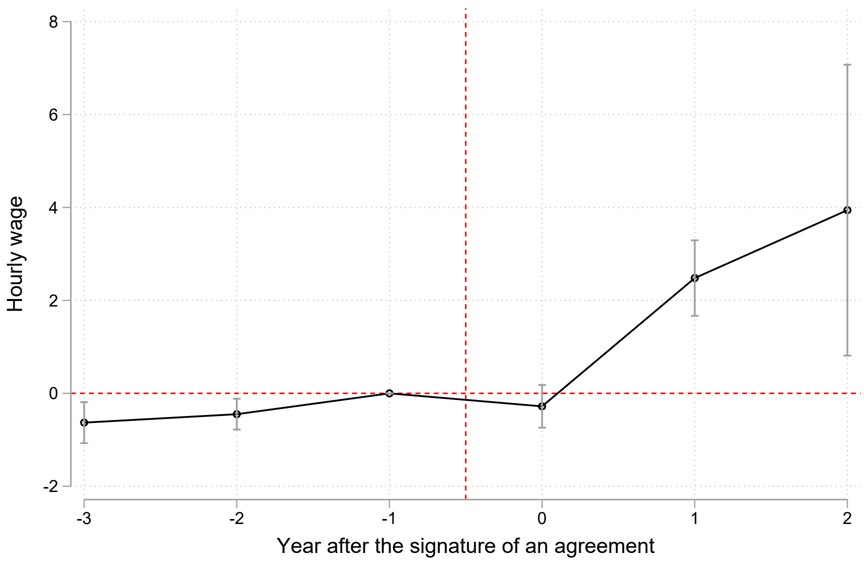
Notes: 95% confidence intervals. This graph reports the β_j coefficients from the estimation of Eq. 1 on firms. Average outcome one year before treatment: a); 171.0 b); 115.4 c) 1010.0.

Figure A30: Event-study graph on hourly wage (log) for new hires.



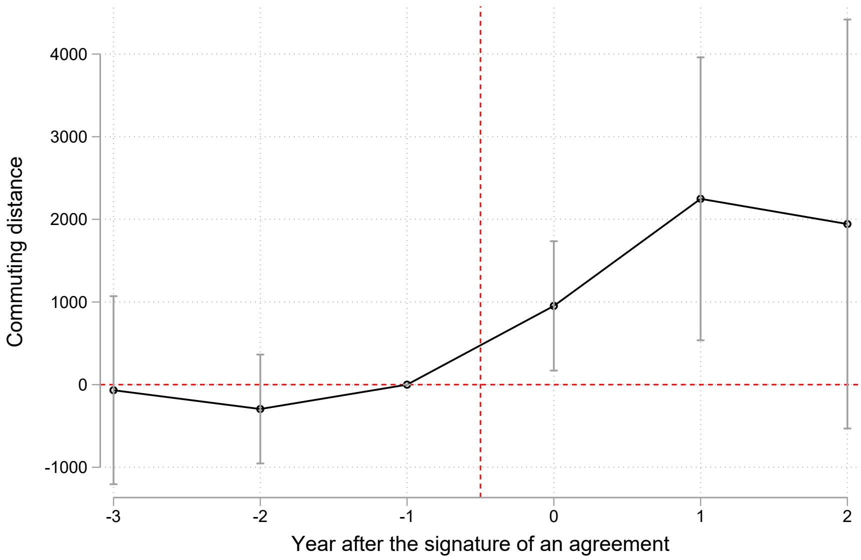
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 for the sample of new hires. Average outcome one year before treatment: 3.1.

Figure A31: Event-study graph on hourly wage for new hires.



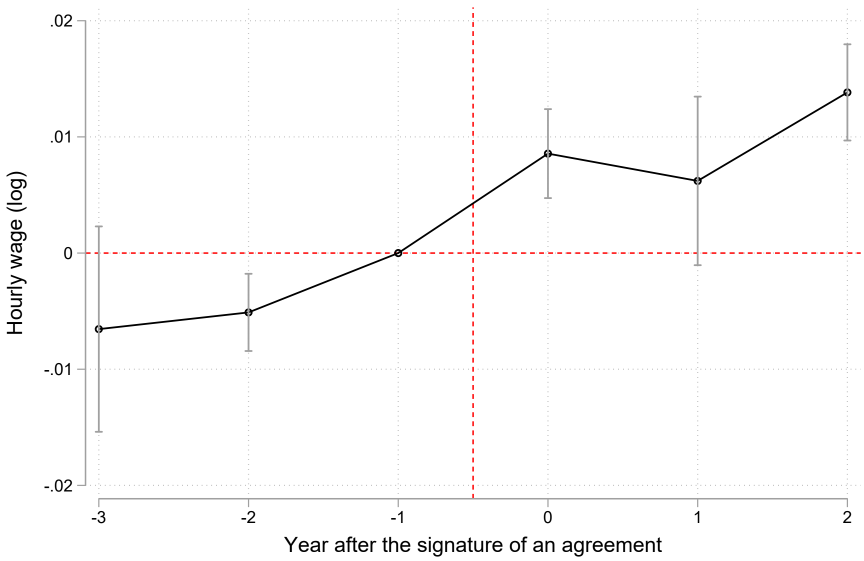
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 for the sample of new hires. Average one year before treatment: 26.9.

Figure A32: Event-study graph on commuting distance for new hires.



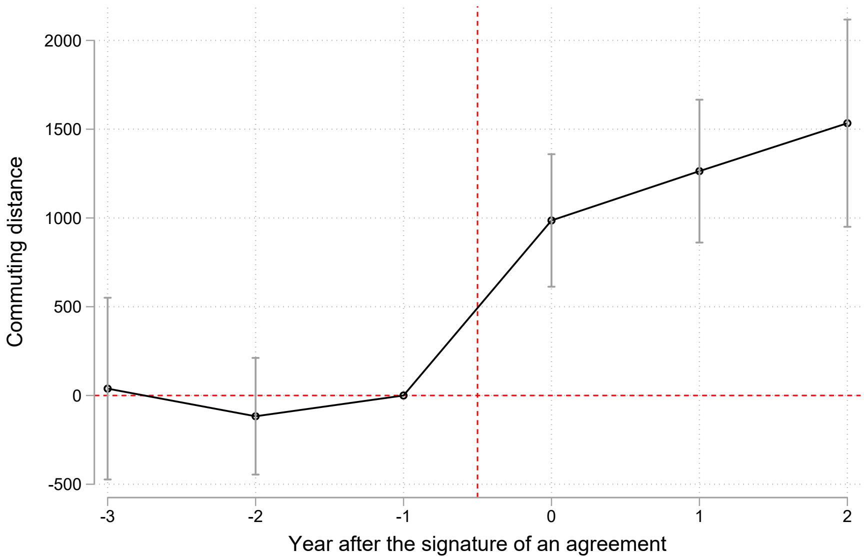
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 for the sample of new hires. Average one year before treatment: 49452.8.

Figure A33: Event-study graph on log hourly wage on the matching sample



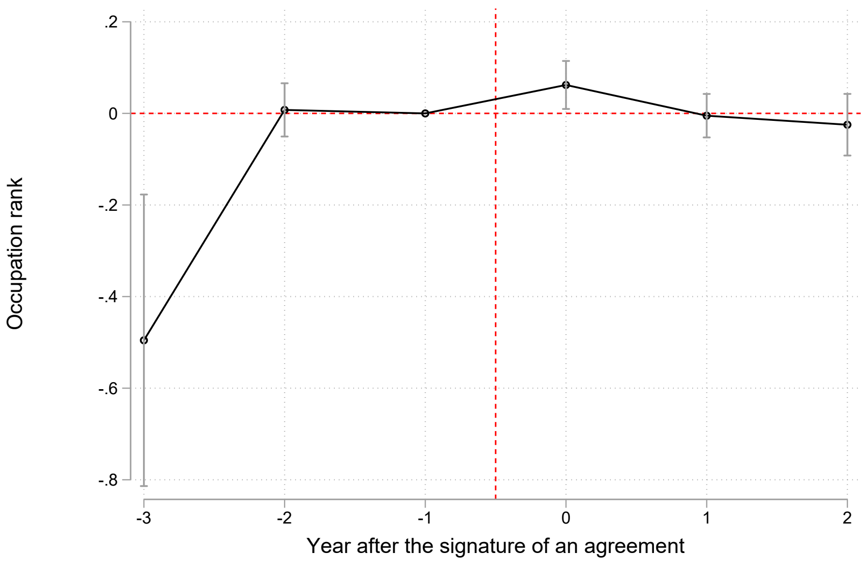
NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on log hourly wage in levels for the sample of matched treated and control individuals. Average outcome one year before treatment: 3.3.

Figure A34: Event-study graph on commuting distance (meters) on the matching sample



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on commuting distance for the sample of matched treated and control individuals. Average outcome one year before treatment: 33525.1.

Figure A35: Event-study graph on occupation rank on the matching sample



NOTE: this graph reports the β_j coefficients from the estimation of Eq. 1 on occupation rank for the sample of matched treated and control individuals. Average outcome one year before treatment: 22.8.