Teleworking and Workers' Careers

Lorenzo Incoronato
University of Naples Federico II, CSEF, RFBerlin

Vincenzo Pezone
Luiss University

Annalisa Scognamiglio
University of Naples Federico II, CSEF, IFN

March 25, 2026

Preliminary draft. Please do not circulate.

Abstract

We examine the impact of work-from-home (WFH) arrangements on workers' earnings and careers. Using Dutch administrative data matched to survey-based WFH information, we document the persistence of hybrid WFH in teleworkable occupations after the pandemic. Workers in these occupations experience a 7% rise in labor earnings compared to observationally similar workers in non-teleworkable jobs. The wage increase is driven by more hours worked and, to a lesser degree, higher hourly wages. We also observe higher job mobility for workers in teleworkable jobs, and the earnings effects are especially pronounced among job movers. We provide suggestive evidence that WFH has favored assortative matching in the labor market.

*We thank Philipp Kircher, Marco Pagano, Paul Redmond, and audiences at University of Naples Federico II, Badolato Labor and Organization Workshop, RFBerlin-CReAM Workshop, and the TRAILS 4th Plenary Meeting for their comments and suggestions. This project was supported by the TRAILS project, financed by the European Union's Horizon Europe research and innovation program under grant agreement No 101132673.

1 Introduction

The rise of work-from-home (WFH) has been among the most dramatic shifts occurred in labor markets around the world in recent years. The share of days worked from home in the United States has increased from 7% in 2019 to 28% in 2023, and similar developments have taken place—albeit to a lower extent—in other countries (Barrero et al., 2023). Importantly, remote work is predicted to stay in the long run (Barrero et al., 2021). This has sparked a large amount of research on the consequences of WFH. Economists broadly consider WFH as a job amenity subject to negotiation between firms and their employees (Aksoy et al., 2022; Hansen et al., 2023; Lee, 2023; Cullen et al., 2025). In turn, the increased adoption of WFH arrangements may have impacted the careers of individuals who can work remotely, by affecting not only wages at their *current* employers, but also job mobility . Moreover, to the extent that WFH has contributed to enlarging the relevant labor market for workers and firms, it may also have improved matching efficiency by allowing workers to access better-fitting jobs and firms to hire from larger pools of workers (Coskun et al., 2024; Akan et al., 2025).

To date, there is still limited knowledge about the effect of WFH on workers' careers. The existing empirical research on the effects of WFH largely consists of descriptive, survey-based studies or single-firm experiments. However, understanding how individual careers have evolved following the advent of WFH requires longitudinal data tracking workers across different jobs—possibly matched with WFH information. In this paper, we leverage administrative matched employer-employee data combined with survey-level information on WFH take-up for the Netherlands—the European country with the highest WFH rate (Achard et al., 2025). The data report detailed occupation categories, which we classify based on the feasibility of working from home using the classification introduced by Dingel and Neiman (2020)—which assigns a teleworkability index to each occupation based on job tasks and required technologies.

We begin by assessing whether this measure of teleworkability predicts the adoption of WFH arrangements after the pandemic. We compare WFH rates—as reported in individual-level repeated cross-section survey data—for workers in teleworkable versus non-teleworkable occupations, before and after 2019, and controlling for occupation fixed effects, as well as a set of worker- and firm-level characteristics. We find a stark and persistent increase in WFH after the pandemic for workers in teleworkable occupations, specifically for hybrid WFH arrangements. WFH rates increased by 15 percentage points in teleworkable jobs compared to non-teleworkable ones in 2020. While we observe a partial reversion of the effect for full WFH, the impact on partial WFH appears persistent

even three years after the onset of the pandemic.

Having established a persistent rise in WFH use in teleworkable jobs, we move to the analysis of worker-level panel data in the main empirical exercise. We run two-way fixed effects models comparing workers who had a teleworkable occupation in 2019 (treated group) to workers who had a non-teleworkable occupation (control group), as in, e.g., Bloom et al. (2024a). As workers in the two groups are different in several dimensions, such as earnings, we match each treated worker to a statistical "twin" based on pre-pandemic characteristics, namely lagged wages, tenure, industry, firm size, age, and gender. We then estimate our difference-in-differences model on a balanced sample of about 12,200 workers.

We first investigate the effects on wages. Workers in teleworkable jobs display a large increase in labor earnings, relative to their matched controls in non-teleworkable jobs, with long-run wage gains of almost 7 logpoints four years after the pandemic. The wage increase is, in large part (5 logpoints), accounted for by a rise in hours worked, although there are also significant long-run gains in hourly wages (2 logpoints). We do not detect significant effects on overall employment probabilities—implying an overall increase in total labor earnings (of roughly 2,600€) fully induced by the positive effect on wages.

This empirical design relies on the validity of the parallel trends assumption being satisfied, conditional on matched covariates. Yet, demand-side factors, such as automation and the rise of artificial intelligence, may be correlated with teleworkability and influence outcome dynamics, possibly confounding the estimated coefficients. We perform a number of robustness tests to rebut these concerns. First, we rely on the detailed information on educational achievement present in the CBS database to reestimate the event-study regressions after excluding STEM graduates, who might have disproportionately benefited from the rise of new technologies, such as artificial intelligence. Second, we exclude workers in occupations at low risk of automation, whose earnings might have been less negatively affected by technological developments. Our results remain similar to those estimated in the full sample. Moreover, the zero effect found on employment probabilities rules out another possible concern—that workers in non-teleworkable occupations suffered higher job losses after the pandemic, with potential "scarring" effects on their earnings and careers.

We then investigate whether the availability of WFH after the pandemic did indeed expand the labor market available to workers in teleworkable occupations. While treated and control workers are equally likely to remain employed after 2019, they differ in their probabilities of retaining their pre-pandemic jobs. Individuals in teleworkable occupations are about 5 percentage points less likely to keep their pre-pandemic employer than

those in the control group. Motivated by this result, we separately investigate the earnings effects for "stayers" (workers who keep their 2019 employer until the end of the sample period) and "leavers" (those who eventually move to a new employer). We find that the positive effects on earnings and hours discussed above are driven by workers who eventually leave their pre-pandemic employer.

These results suggest the presence of large gains from mobility for workers in teleworkable jobs, which leads us to investigate these job transitions more closely. We estimate firm-specific and worker-specific wage premia, following Abowd et al. (1999)'s approach, for the pre-pandemic period, and collect the estimated firm and worker fixed effects. We then use this firm wage premium as the outcome variable in our difference-in-differences model. We find evidence of a small positive effect, suggesting that workers leaving their prepandemic jobs tend to move to high-paying firms at a larger rate when they have teleworkable occupations. While coefficients are statistically insignificant in the full sample, we find strong positive effects when focusing solely on high-ability workers—identified as those with above-the-median worker fixed effects. Conversely, we do not find effects for low-skill workers, suggesting that they have been unable to take advantage of the opportunities offered by WFH availability. Our interpretation is that WFH appears to have facilitated assortative matching in the labor market, allowing high-wage workers to sort into high-wage firms.

This paper contributes to the growing body of research on WFH and its effects on labor markets. Much of this literature has focused on how WFH impacts productivity and the functioning of organizations, typically finding mixed evidence based on workers' skills and tasks, firm structure, and specific WFH arrangement (i.e., full-time or hybrid WFH). The existing studies are either based on descriptive, survey-level data (Etheridge et al., 2020; Barrero et al., 2021; Criscuolo et al., 2021), or leverage experiments in individual firms (Bloom et al., 2015; Atkin et al., 2023; Gibbs et al., 2023; Angelici and Profeta, 2024; Choudhury et al., 2024; Emanuel and Harrington, 2024; Bloom et al., 2024b). There is, in contrast, very little evidence on the longitudinal effects of the rise of WFH on workers' careers.

Goux and Maurin (2025) examine a 2017 law that promoted WFH arrangements in France, and find a deterioration in workers' health outcomes; Achard et al. (2025) leverage variation in WFH rights based on collective labor agreements in the Netherlands, showing improved school attainments of children when their parents work from home. Interestingly, both studies document limited direct effects on wages and other labor market outcomes of affected workers. Most importantly, their primary focus is not on the effect of WFH on workers' mobility and career changes. Arntz et al. (2022) track remote

employees in Germany and provide descriptive evidence of a higher propensity to switch jobs among them. Our work builds on the existing evidence, but our data allow us to track workers' careers in the long run, up to four years after the start of the pandemic, and to leverage variation in WFH availability across occupations to provide causal estimates of the impact of WFH on careers, mobility, and labor market matching.

The paper is structured as follows. Section 2 describes the data; Section 3 discusses the empirical design and assumptions; Section 4 shows the baseline results. The last section concludes.

2 Data

This paper uses three separate data sources: matched employer-employee data from social security archives, survey-level data, and occupation-level teleworkability indices. We describe each data source and how we combine them to obtain our final dataset in more detail below.

2.1 Social Security Data

Our main data source is the matched employer-employee administrative dataset covering the entire Dutch workforce, maintained by the National Statistical Office (*Centraal Bureau voor de Statistiek, or CBS*). The data report information on workers' wages, earnings, and hours worked, as well as demographic information, such as gender and age. We can also access detailed information on individuals' education for almost 90% of our sample, provided via the International Standard Classification of Education (ISCED) maintained by UNESCO. The ISCED code enables us to identify both the educational attainment (elementary school, high school, vocational school, bachelor's or master's degree, doctorate, etc.) as well as the field of study. For workers employed in the private sector, we also have access to employers' balance sheet data, which we primarily use to identify their industry.

In our baseline analysis, we focus on four key outcomes. *Wage* corresponds to the labor income earned by the worker in that year. If the worker is employed by multiple employers, we retain the job with the highest income. *Hours* refer to the hours worked in that employment spell during the year. The *hourly wage* is calculated as the ratio of labor income to hours worked, again retaining only the job spell with the highest income. Finally, *earnings* refer to the total labor income earned throughout the year, possibly across multiple employers. Earnings are set to zero if the employee does not earn any labor income.

2.2 Survey Data

Two second key data sources are the CBS' National Survey on Working Conditions (*Nationale Enquête Arbeidsomstandigheden*, henceforth NEA) and the Labor Force Survey (*Enquête beroepsbevolking*, henceforth EBB). Both are conducted every year over repeated cross sections of workers, and cover about 40,000–60,000 and 120,000-150,000 individuals, respectively.

Crucially, the surveys report information on workers' occupations, classified using 4-digit ISCO codes. The NEA survey also reports information on whether workers work from home and, if so, how frequently.[1] Specifically, survey respondents are asked "How many hours do you work from home for your employer on average per week?" They are given five potential options, namely: (i) I usually work at my own home address; (ii) I usually work at the fixed address of the employer and also at home; (iii) I usually work in different places and also at home; (iv) I usually work at the employer's permanent address and not at home; (v) I usually work in different places and not at home. We classify participants who choose option (i) as only working from home, whereas participants choosing options (ii) or (iii) are classified as performing *some* work from home.

2.3 The Teleworkability Classification

To classify occupations into teleworkable or not teleworkable, we use the well-established Dingel and Neiman (2020)'s index for the probability a job can be performed from home.[2] This is an ex-ante teleworkability measure, constructed using information about job tasks and required technology prior to the pandemic and regardless of actual WFH rates in each occupation.

Notice that we chose not to develop our own teleworkability classification. A drawback of this approach is that there could potentially be more robust taxonomies (see Wiebe, 2025, for a discussion), or better suited to the context we study. The key advantage of using an existing classification are that it mitigates concerns about data mining.

Dingel and Neiman (2020) define this index for 2-digit O*Net occupations. To merge the index into our data, we use a O*Net-ISCO crosswalk made available by the O*NET Resource Center, an organization sponsored by the U.S. Department of Labor. Unfortunately, the match is not "one-to-one," meaning each ISCO code is often matched with more

[1] Participants in the EBB survey are asked a similar question; however, the data report the additional category "Unknown" for 80% of the participants, raising concerns regarding the representativeness of the subsample for which the answer is not missing. For this reason, we discard participants in the EBB survey from the analysis presented in Section 4.1.

[2] This classification has proved extremely popular in recent work. See for example Gottlieb et al. (2021), Papanikolaou and Schmidt (2022), Bartik et al. (2025), and Jones et al. (2021), among others.

than one O*Net code. As a conservative choice, we therefore keep in our analysis only ISCO codes for which all the matched O*Net codes have teleworkability index of either zero or one. While this procedure roughly halves our sample, leaving us with workers in 71 unique 3-digit ISCO codes, it allows us to unequivocally classify occupations as either teleworkable or not.

3 Econometric Framework

We structure our empirical analysis in two parts. In the first part, we aim to assess whether our teleworkability classification predicts *actual* WFH across occupations after the pandemic. In the second part, we study whether being employed in a teleworkable occupation before the onset of the pandemic affects wages and earnings in the subsequent years.

3.1 Occupation-Level Design

As noted in Section 2.2, the NEA survey includes a question on whether participants work from home. We combine this information with data on demographics, firm characteristics and, importantly, occupations (at the 3-digit ISCO code). Unfortunately, the dataset has a repeated cross section structure, meaning that we cannot follow the same individual over time and cannot, therefore, include individual fixed effects in the regression model. However, the survey does include a rich set of covariates, which we use in our regression model, which reads as follows:

$$y_{ijt} = \sum_{\tau=2014(\neq 2019)}^{2023} \beta_\tau \cdot 1\{t = \tau\} \cdot Teleworkability_j + \alpha_j + \gamma_{sakgt} + \epsilon_{ijt} \tag{1}$$

i, j and t index workers, occupations and years, respectively. The outcome variable y is an indicator taking value of one if a worker declares to work from home, either fully or partially. We include a vector of occupation fixed effects α_j, as well as the vector γ_{sakgt}, denoting firm size bin s × age bin a × industry k × gender g × year t fixed effects.[3]

The coefficients of interest β_τ denote the difference in WFH rates between teleworkable and non-teleworkable occupations, indicated by the $Teleworkability_j$ binary variable,

[3]The NEA survey classifies firms' size in nine bins (1-4; 5-9; 10-19; 20-49; 50-99; 100-249; 250-499; 500-999; 1,000 or more employees) and workers' age in six age classes (15-25; 25-35; 35-45; 45-55; 55-65; and 65-75 years old). Industry is defined using the 2008 Dutch Standard Business Classification (*Standaard Bedrijfsindeling*, SBI 2008), which corresponds to the European Union 2-digit NACE, revision 2.

relative to the difference in 2019, which is normalized to zero. We cluster standard errors at the 3-digit occupation level.

3.2 Worker-level Design

In the main empirical exercise of the paper, we compare the labor market outcomes for workers in teleworkable occupations (treatment group) versus workers in non-teleworkable occupations (control group), before and after the pandemic. We thus use the employer-employee matched dataset, which covers the universe of the Dutch workforce. Information on the workers' occupation is available, however, only in the EBB and NEA surveys; therefore, we require the workers to be observed in the 2019 waves of either survey. Finally, we also require the workers' occupations to be unequivocally classifiable as either teleworkable or not teleworkable (see the discussion in Section 2.3). These restrictions result in a starting sample of 47,253 unique individuals, 22,016 of whom are in the treatment group and 25,237 in the control group.

A simple comparison of the careers of individuals in teleworkable and non-teleworkable jobs is unlikely to be informative, as these two groups of workers are hardly comparable. As shown in the first three columns of Table 1, wages of workers in teleworkable occupations are almost 30 logpoints higher already prior to the pandemic. This is not surprising: The teleworkability index devised by Dingel and Neiman (2020) captures a job's feasibility to be performed remotely, and therefore reflects technological factors and the specific tasks required. Teleworkable occupations include, for example, mathematicians, actuaries and statisticians (ISCO code 212), and electrotechnology engineers (ISCO code 215), among others, which are likely to be performed by high-skill workers. Workers in teleworkable occupations are also 13 percentage points more likely to be women, and their firm's size is 26 logpoints smaller.

To tackle these issues, we perform a simple matching exercise, where each treated worker is matched to a control worker with similar observable characteristics. To exclude workers characterized by high job turnover, we narrow our focus to individuals with at least two years of tenure at their 2019 firm. Then, we fit a propensity score algorithm based on the following matching variables: logarithm of wage in 2019 and 2018, worker's age, and logarithm of firm size (that is, total firm employment). Before estimating the model, we winsorize all the continous variables at the 1 percent level. We fit this model for each gender $\times$ tenure at the firm $\times$ industry cell, meaning that we match *exactly* on these categorical characteristics.[4] Treated workers are matched with control workers with

[4] As our data start in 2010, the tenure variable is severely censored. For this reason, we simply compute an "above-the-median" tenure dummy and match exactly on this variable.

the closest propensity score, without replacement, with a maximum difference in the propensity scores (caliper) of 0.05. This procedure delivers a balanced sample of 12,196 workers, half of which (6,098) are in the treatment group. For our analysis, we focus on a symmetric 9-year window around the first pandemic year, 2020.

Columns 4 through 6 of Table 1 report the descriptive statistics for the resulting matched sample. The marked differences observed in the full sample (columns 1–3) are not present anymore. Wages differ by just about 3 logpoints and are, if anything, slightly higher for workers in non-teleworkable occupations. Differences in firm size and age are negligible and insignificant as well.

While we explicitly match on these variables, the bottom part of Table 1 shows thar there are small and insignificant differences also for variables we do not target in our matching algorithm. Treated and control workers are similar in terms of hourly wages, hours, earnings, and in the likelihood of having a permanent contract. This confirms that our matching strategy has been successful.

Our key regression equation, estimated on the matched sample, is the following:

$$y_{it} = \sum_{\tau=2016(\neq 2019)}^{2024} \beta_\tau \cdot 1\{t = \tau\} \cdot Teleworkability_{j(i)}^{2019} + \alpha_i + \gamma_t + \epsilon_{it}, \tag{2}$$

Again, i, j and t index workers, occupations and years, respectively. Because we now use worker-level panel data, we can control for a vector of worker fixed effects α_i. We also include a vector of year dummies γ_t. The event-study coefficients β_τ now denote the difference in outcome y (e.g., earnings) between a worker in a teleworkable occupation in 2019, as indexed by the indicator variable $Teleworkability_{j(i)}^{2019}$, and a worker in a non-teleworkable occupation in 2019, relative to the 2019 difference in outcomes, which is normalized to zero. Again, we cluster standard errors at the 3-digit occupation level. y_i is a labor market outcome. We mostly focus on the logarithm of wage or hourly wage, the logarithm of hours, and earnings. In subsequent analyses, we will also examine the effects of teleworkability on employment, job-to-jo transitions, and wage premia. We postpone the definitions of the relevant outcome variables for these tests to Sections 4.4 and 4.5.

4 Results

This section discusses the main results. We begin by providing evidence of higher incidence of WFH in teleworkable occupations. Having established this, we study the earnings and career trajectories of workers in these occupations, with a key focus on their

job mobility in the years after the pandemic.

4.1 Teleworkability and Postpandemic Work-from-Home

Figure 1 plots the vector of event-study coefficients resulting from the estimation of Equation (1), together with corresponding 95% confidence intervals. In this setting, we are testing whether individuals in teleworkable occupations exhibit a higher propensity to work from home after the pandemic. The outcome is a binary indicator taking value of one in the case of full WFH (Panel a), or hybrid WFH (Panel b). Table 2 reports the corresponding event-study coefficients for the contemporaneous (2020) and the long-run (2023) effect.

First, we find that both event studies exhibit reasonably parallel trends: All the prepandemic coefficients are close to zero and insignificant, except for those corresponding to 2014, which are, however, fairly small in magnitude. As the pandemic hits, we detect a stark and immediate rise in WFH rates of about 15 percentage points for workers employed in teleworkable occupations, relative to the control group. These are very large effects, compared to baseline levels of 1.4% for full WFH and 14.6% for hybrid WFH (see Table 2 Column 1 and 2, respectively).

We also detect marked differences in the *persistence* of the effects for the two outcomes. In the case of full WFH, the coefficients drops by two thirds, to just 5 percentage points in 2023. Hence, as the emergency measures imposing individuals to work remotely were phased out, the incidence of full teleworking decreased. At the same time, hybrid WFH arrangements have remained a permanent feature of labor markets. By 2023, we find little evidence of a decay in the effect of the pandemic on partial WFH rates for workers in teleworkable occupations.

This set of results leads to two conclusions. First, teleworkability is a strong predictors of the evolution of WFH rates after the pandemic, validating the approach that we adopt in the baseline analysis that follows. Second, teleworkability appears to have led to a persistent rise in the availability of partial, rather than full WFH. Hence, our results should be interpreted as the effect of a *reduction* in commuting costs, rather than in their complete elimination.

4.2 Teleworkability and Labor Market Outcomes

We now compare workers in teleworkable occupations to their matched controls in non-teleworkable occupations in 2019, leveraging the previous findings of a rise in WFH rates for the former group. Figure 3 displays event-study coefficients for the key labor market

outcomes; we report contemporaneous (2020) and long-run (2024) effects in Table 3.

Figure 3 Panel (a) shows no differential pre-trends in log wages for treated and control workers before 2019—which points against possible demand-driven confounding factors. Following the pandemic, workers in teleworkable occupations significantly outperform those in the control group. Indeed, four years after the pandemic, we find that their wages rise by 6.6 logpoints. This effect is significant at the 1% level (Table 3 Column 1).

We then decompose this wage premium into two components, namely hours and hourly wage. In Figure 3 Panel (b), where the dependent variable is the logarithm of hours worked, the long-run effect of the pandemic on workers in teleworkable occupations is equal to 4.6 logpoints (Table 3 Column 2). The effect on the hourly wage is also significant but smaller, and equal to 0.021 (Figure 3 Panel (c) and Table 3 Column 3). Hence, the increase in wages is largely explained by an increase in the intensive margin of labor supply, with the remaining one third accounted for by a higher hourly wage.

Finally, we investigate whether these wage effects also translate into higher total earnings. Panel b of Figure 3 and Table 3 Column 4 show that, four years after the event year, earnings increase by 2,600€. This is a meaningful effect, compared to the pre-sample average earnings for treated workers of 40,500€ (see Table 1).

4.3 Robustness Checks

This empirical design relies on a standard parallel trends assumption. We require that, conditional on our matched variables, outcomes would have evolved in the same way for workers in teleworkable versus non-teleworkable occupations, in the absence of the pandemic. In this section, we discuss possible threats to this assumption and present additional tests that support our identification strategy.

First, recent research has documented that demand-side shifts such automation (Acemoglu and Restrepo, 2022, and Acemoglu and Restrepo, 2019) and the rise of artificial intelligence (Acemoglu et al., 2022, and Acemoglu and Johnson, 2024) have had significant effects on the job market, which might in turn differ between teleworkable and non-teleworkable occupations. This is a plausible possibility, as the teleworkability of a job is related to its technological content and tasks. In turn, this would imply that observed effects on wages and careers of treated workers relative to control ones after the pandemic reflect not just the increased diffusion of WFH in teleworkable jobs, but also shifts in the demand for those workers. In Panel (a) of Figure 3, we plot the employment share of workers in teleworkable occupations, using again data from the NEA and EBB surveys.[5]

[5]For this graph, we plot the number of employees in teleworkable occupations scaled by the total number of employees included in the surveys. As discussed in Section 2.3, the mapping between the Dingel and

The share of employees in teleworkable occupations does not appear to increase abruptly after the pandemic, despite being on a slightly rising trend, suggesting the lack of sudden shifts in relative demand after the pandemic.[6] Most importantly, our matching algorithm imposes treated and control workers to be in the *same industry*, and therefore likely subject to the same demand shocks.

A second concern is that the Covid-19 shock to labor markets was broad, and not limited to the structural increase in the use of WFH arrangements. While this would not be a concern for our approach if this shock affected teleworkable and non-teleworkable occupations in the same way, it is possible that the pandemic led to higher job loss rates for workers in non-teleworkable occupations. Even if just temporary, job loss could lead to scarring effects and affect individual career prospects (Davis and Von Wachter, 2011). In Panel (b) of Figure 3, we reestimate Equation 2 using as the dependent variable an "employed" dummy, that is, a dummy equal to one if the worker earns nonzero labor income in that year. We find no differential job loss probabilities between the two groups in the matched sample; if anything, workers in teleworkable occupations exhibit slightly lower employment probability at the onset of the pandemic, but this difference quickly fades away. This is not surprising, given the extensive relief measures implemented in the Netherlands after the outbreak of the pandemic (OECD, 2021).[7]

We can also more directly address the confounding factors by excluding the workers who are more likely to be affected by contemporaneous technological shocks. In Figure 4 we replicate our baseline analysis for both the full sample (in blue) and the subsample of workers for which educational achievement is known and that do not have a STEM degree.[8] For the four key outcomes we examine, excluding workers with a STEM education produces virtually identical results.

Another key concern that we seek to address is that workers in teleworkable occupations are those least exposed to the risk of automation, which might have differentially affected their earnings. To rule out this possibility, we make use of the "automation ex-

Neiman (2020)'s teleworkability classification and the ISCO codes is not unequivocal. If we only include in the denominator of the ratio only workers for which teleworkability is either 0 or 1, the share is obviously higher, but we obtain qualitatively similar conclusions.

[6]Evidence from Italy (Bratti et al., 2024) documents instead a positive, but very short-lived, shift in demand for teleworkable occupations right after the pandemic.

[7]Indeed, the national employment rate went down by just 0.4% in 2020, and already in 2021 bounced above its prepandemic levels.

[8]Out of the starting sample of 12,196 workers, we know the educational attainment of 10,710 individuals (5,404 in the treatment group and 5,306 in the control group). From this subsample, we exclude 947 individuals with a STEM education (673 in the treatment group and 274 in the control group), resulting in a final "No STEM" subsample of 9,763 individuals (5,032 in the control group and 4,731 in the treatment group).

posure" classification developed by the Labor Market Information (LMI) Institute,[9] and exclude all the workers who are classified as having the lowest automation risk (i.e., automation risk category 1 according to the LMI's taxonomy).[10] If the low exposure to automation risk was indeed driving the results, the differences in post-pandemic outcomes between the treatment and control groups should be significantly attenuated. However, as Figure 5 shows, excluding these workers produces nearly identical results.

We conclude that the outperformance of workers in teleworkable occupations in the years following the pandemic is a robust result, unlikely to be driven by the most plausible confounding factors.

4.4 Retention, Stayers, and Leavers

We have established that the advent of WFH has led to higher earnings for individuals in teleworkable occupations, led to both more hours worked and, to a lower extent, higher hourly wage. We now investigate whether treated workers are more or less likely to retain their jobs. These tests are motivated by the hypothesis that the diffusion of teleworking has broaden the potential labor market for jobs that can be performed at home.

We re-estimate Equation 2, this time with a dummy equal to one if the employee is employed with their prepandemic employer. As we are interested in the propensity to engage in job-to-job transitions, we only include employed workers in these regressions. As shown by the event-study coefficients of Figure 6 and Table 4 Column 1, we document *lower* retention rates for treated workers, which are, by 2024, 5.1 percentage points more likely to have left their 2019 job than their matched controls in non-teleworkable jobs. This is a fairly large effect, as compared to a retention rate of workers in the control group of 65.8% four years after the pandemic.

4.5 Which Workers Move, and Where?

Having established that WFH availability has increased job mobility for affected workers, we now seek to understand whether there are gains from such mobility by better characterizing job transitions. We focus on firm wage premia as the outcomes, computed using the methodology introduced by Abowd et al. (1999), which is widely adopted in the literature (see, e.g., Card et al., 2013).

[9] The data can be accessed at `https://www.lmiontheweb.org/automation-exposure-score/`.

[10] Our sample includes 2,200 workers with the lowest automation risk (1,755 in teleworkable occupations and 445 in non-teleworkable occupations). Hence, the resulting sample comprises 9,996 workers (4,343 in teleworkable occupations and 5,653 in non-teleworkable occupations).

We first regress the logarithm of the hourly wage on worker and firm fixed effects, as well as year fixed effects and a cubic polynomial in worker's age. Following Abowd et al. (1999), our estimation is conducted in the largest connected set. Importantly, we conduct our estimation on the full CBS sample for the 2010–2019 window. Hence, we do not include the pandemic and postpandemic years to prevent our inferences from being contaminated by the increase in teleworking occurred after the pandemic.

In Panel (a) of Figure 7 and Table 4 Column 2, the dependent variable is the firm wage premium. We detect, as expected, some evidence that workers in teleworkable occupations move towards high-paying firms. However, the estimates do not allow us to draw meaningful conclusions, with all the postevent coefficients being weakly significant at most. Yet, this result masks substantial heterogeneity. To test whether this effect differs in terms of workers' ability, we distinguish between workers with above- versus below-median estimated AKM *worker* fixed effect, our proxy for workers' skill. We then report event-study coefficients for these two subsamples in Figure 7 Panel (b) and Table 4 Columns 3-4. For high-ability workers (depicted in red in Figure 7), we estimate a positive and significant effect, with a long-run coefficient equal to 0.7 logpoints, significant at the 1 percent level. Conversely, there are no effects for low-ability workers. These results suggest that WFH has improved assortative matching in labor markets, allowing high-wage workers to match with high-wage firms.

This finding point to possible gains from job mobility. To investigate this, we proceed as follows. We define workers as "stayers" if they retain their 2019 employer throughout the years 2020–2024. "Leavers" are instead the workers that are employed at a different firm in any of these five years.[11] Event-study coefficients for these two subsamples are reported in Figure 8 and Table 5 for the four main outcomes. We find sharp differences in the postpandemic outcomes for leavers and stayers. Leavers in teleworkable occupations outperform leavers in non-teleworkable occupations by 11.8 logpoints four years after the pandemic; the analoguous figure is 3.1 logpoints for stayers. The long-run coefficients in the leavers sample for log(hours), log(hourly wage), and earnings are 0.081, 0.038, and 4,371, respectively, all significant at the 1 percent level. The long-run coefficients in the leavers sample are instead smaller in magnitude and less precisely estimated, being even insignificant when the outcomes are the logarithm of the hourly wage and earnings.

[11]The sample of stayers includes 7,911 unique workers (4,036 in the control group and 3,775 in the treatment group). The sample of leavers includes 4,385 workers (2,062 in the control group and 2,323 in the treatment group).

5 Conclusions

This paper leverages administrative employer-employee matched data from the Netherlands to document the effects of "teleworkability," that is, the possibility of performing a given occupation from home, on the postpandemic careers' trajectories. First, we document that firms in teleworkable occupations exhibit higher rates of WFH after the pandemic, with an especially persistent effect for partial WFH arrangements.

In our main analysis, we show that workers in teleworkable occupations display large wage gains after the pandemic. These effects are not driven by a higher prevalence of workers with STEM education in teleworkable occupations, not to a lower vulnerability of their jobs to automation. Morever, they cannot be explained by differences in job loss rates, although workers in teleworkable occupations are more likely to engage in job-to-job transitions. A main contributor is the increase in hours worked, suggesting that commuting times might constrain the extensive margin of the labor supply. In addition, we find evidence of assortative matching, as high-skill workers tend to move to firms characterized by higher wage premia. This suggests that the diffusion of WFH has widened the range of potential employers available to workers, and that these new opportunities are taken up especially by the most skilled workers.

References

Abowd, John, Francis Kramarz, and David Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–334.

Acemoglu, Daron and Pascual Restrepo, "Automation and New Tasks: How Technology Displaces and Reinstates Labor," *Journal of Economic Perspectives*, May 2019, *33* (2), 3–30.

_ **and** _ , "Tasks, Automation, and the Rise in U.S. Wage Inequality," *Econometrica*, 2022, *90* (5), 1973–2016.

_ **and Simon Johnson**, "Learning From Ricardo and Thompson: Machinery and Labor in the Early Industrial Revolution and in the Age of Artificial Intelligence," *Annual Review of Economics*, 2024, *16* (Volume 16, 2024), 597–621.

_ **, David Autor, Jonathon Hazell, and Pascual Restrepo**, "Artificial Intelligence and Jobs: Evidence from Online Vacancies," *Journal of Labor Economics*, 2022, *40* (S1), S293–S340.

Achard, Pascal, Michèle Belot, and Arnaud Chevalier, "When Parents Work from Home," IZA Discussion Papers 17957, Institute of Labor Economics (IZA) June 2025.

Akan, Mert, Jose Maria Barrero, Nicholas Bloom, Thomas Bowen, Shelby R Buckman, Steven J Davis, and Hyoseul Kim, "The New Geography of Labor Markets," Working Paper 33582, National Bureau of Economic Research March 2025.

Aksoy, Cevat Giray, Jose Maria Barrero, Nicholas Bloom, Steven Davis, Mathias Dolls, and Pablo Zárate, "Working from Home Around the World," *Brookings Papers on Economic Activity*, 2022, *53* (2 (Fall)), 281–360.

Angelici, Marta and Paola Profeta, "Smart Working: Work Flexibility Without Constraints," *Management Science*, 2024, *70* (3), 1680–1705.

Arntz, Melanie, Sarra Ben Yahmed, and Francesco Berlingieri, "Working from home, hours worked and wages: Heterogeneity by gender and parenthood," *Labour Economics*, 2022, *76*, 102169.

Atkin, David, Antoinette Schoar, and Sumit Shinde, "Working from Home, Worker Sorting and Development," Working Paper 31515, National Bureau of Economic Research July 2023.

Barrero, Jose Maria, Nicholas Bloom, and Steven J Davis, "Why Working from Home Will Stick," Working Paper 28731, National Bureau of Economic Research April 2021.

Barrero, José María, Nicholas Bloom, and Steven J. Davis, "The Evolution of Work from Home," *Journal of Economic Perspectives*, November 2023, *37* (4), 23–50.

Bartik, Alexander, Zoë Cullen, Ed Glaeser, Michael Luca, and Christopher Stanton, "The Rise of Remote Work Evidence on Productivity and Preferences From Firm and Worker Surveys," *Journal of Economics & Management Strategy*, August 2025, *34* (3), 759–772.

Bloom, Nicholas, Gordon Dahl, and Dan-Olof Rooth, "Work from Home and Disability Employment," NBER Working Papers 32943, National Bureau of Economic Research, Inc 2024.

_ , James Liang, John Roberts, and Zhichun Jenny Ying, "Does Working from Home Work? Evidence from a Chinese Experiment," *The Quarterly Journal of Economics*, 2015, *130* (1), 165–218.

_ , Ruobing Han, and James Liang, "Hybrid working from home improves retention without damaging performance," *Nature*, 2024, *630* (8018), 920–925.

Bratti, Massimiliano, I. Brunetti, A. Corvasce, Agata Maida, and Andrea Ricci, "Did COVID-19 (Permanently) Raise the Demand for "Teleworkable' Jobs?," IZA Discussion Papers 16906, Institute of Labor Economics (IZA) April 2024.

Card, David, Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

Choudhury, Prithwiraj, Tarun Khanna, Christos A. Makridis, and Kyle Schirmann, "Is Hybrid Work the Best of Both Worlds? Evidence from a Field Experiment," *The Review of Economics and Statistics*, 02 2024, pp. 1–24.

Coskun, Sena, Wolfgang Dauth, Hermann Gartner, Michael Stops, and Enzo Weber, "Working from Home Increases Work-Home Distances," IAB-Discussion Paper 202406, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg [Institute for Employment Research, Nuremberg, Germany] April 2024.

Criscuolo, Chiara, Peter Gal, Timo Leidecker, Francesco Losma, and Giuseppe Nicoletti, "The role of telework for productivity during and post-COVID-19: Results from an OECD survey among managers and workers," OECD Productivity Working Papers 31, OECD Publishing December 2021.

Cullen, Zoë, Bobak Pakzad-Hurson, and Ricardo Perez-Truglia, "Home Sweet Home: How Much Do Employees Value Remote Work?," *AEA Papers and Proceedings*, May 2025, *115*, 276–81.

Davis, Steven and Till Von Wachter, "Recessions and the Costs of Job Loss," *Brookings Papers on Economic Activity*, 2011, *42* (2 (Fall)), 1–72.

Dingel, Jonathan and Brent Neiman, "How many jobs can be done at home?," *Journal of Public Economics*, 2020, *189* (C), S0047272720300992.

Emanuel, Natalia and Emma Harrington, "Working Remotely? Selection, Treatment, and the Market for Remote Work," *American Economic Journal: Applied Economics*, October 2024, *16* (4), 528–59.

Etheridge, Ben, Yikai Wang, and Li Tang, "Worker productivity during lockdown and working from home: evidence from self-reports," ISER Working Paper Series 2020-12, Institute for Social and Economic Research Oct 2020.

Gibbs, Michael, Friederike Mengel, and Christoph Siemroth, "Work from Home and Productivity: Evidence from Personnel and Analytics Data on Information Technology Professionals," *Journal of Political Economy Microeconomics*, 2023, *1* (1), 7 – 41.

Gottlieb, Charles, Jan Grobovšek, Markus Poschke, and Fernando Saltiel, "Working from home in developing countries," *European Economic Review*, 2021, *133*, 103679.

Goux, Dominique and Eric Maurin, "Sick of Working from Home?," *The Economic Journal*, 04 2025, p. ueaf025.

Hansen, Stephen, Peter John Lambert, Nicholas Bloom, Steven Davis, Raffaella Sadun, and Bledi Taska, "Remote Work across Jobs, Companies, and Space," NBER Working Papers 31007, National Bureau of Economic Research, Inc 2023.

Jones, Callum, Thomas Philippon, and Venky Venkateswaran, "Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home," *The Review of Financial Studies*, 09 2021, *34* (11), 5188–5223.

Lee, Kangoh, "Working from home as an economic and social change: A review," *Labour Economics*, 2023, *85*, 102462.

OECD, "Towards COVID-19 recovery and greater resilience in Zuid-Holland, The Netherlands," OECD Regional Development Papers 2021.

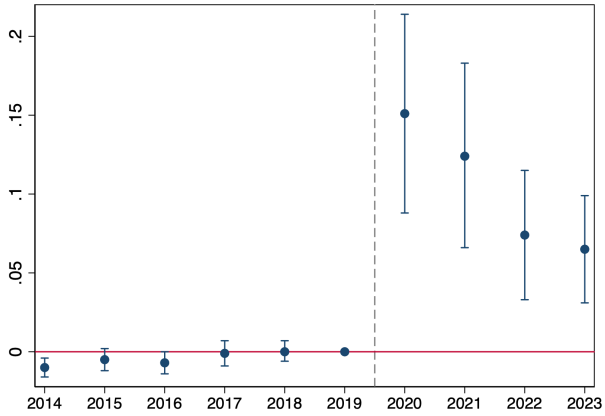
Papanikolaou, Dimitris and Lawrence D W Schmidt, "Working Remotely and the Supply-Side Impact of COVID-19," *The Review of Asset Pricing Studies*, None 2022, *12* (1), 53–111.

Wiebe, Michael, "How many jobs can be done remotely? A reanalysis of Dingel and Neiman (2020)," I4R Discussion Paper Series 232, The Institute for Replication (I4R) 2025.

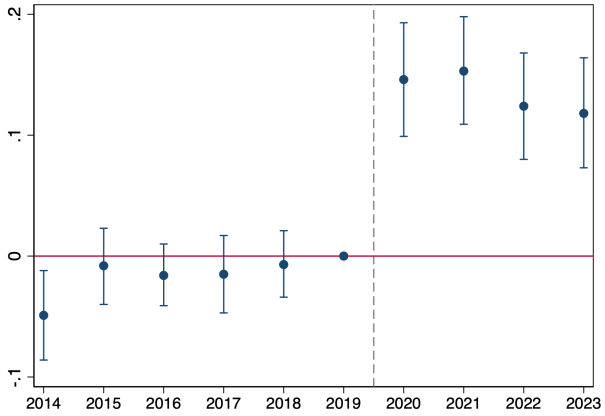
Figures

Figure 1. Teleworkability and Teleworking

(a) Full Teleworking

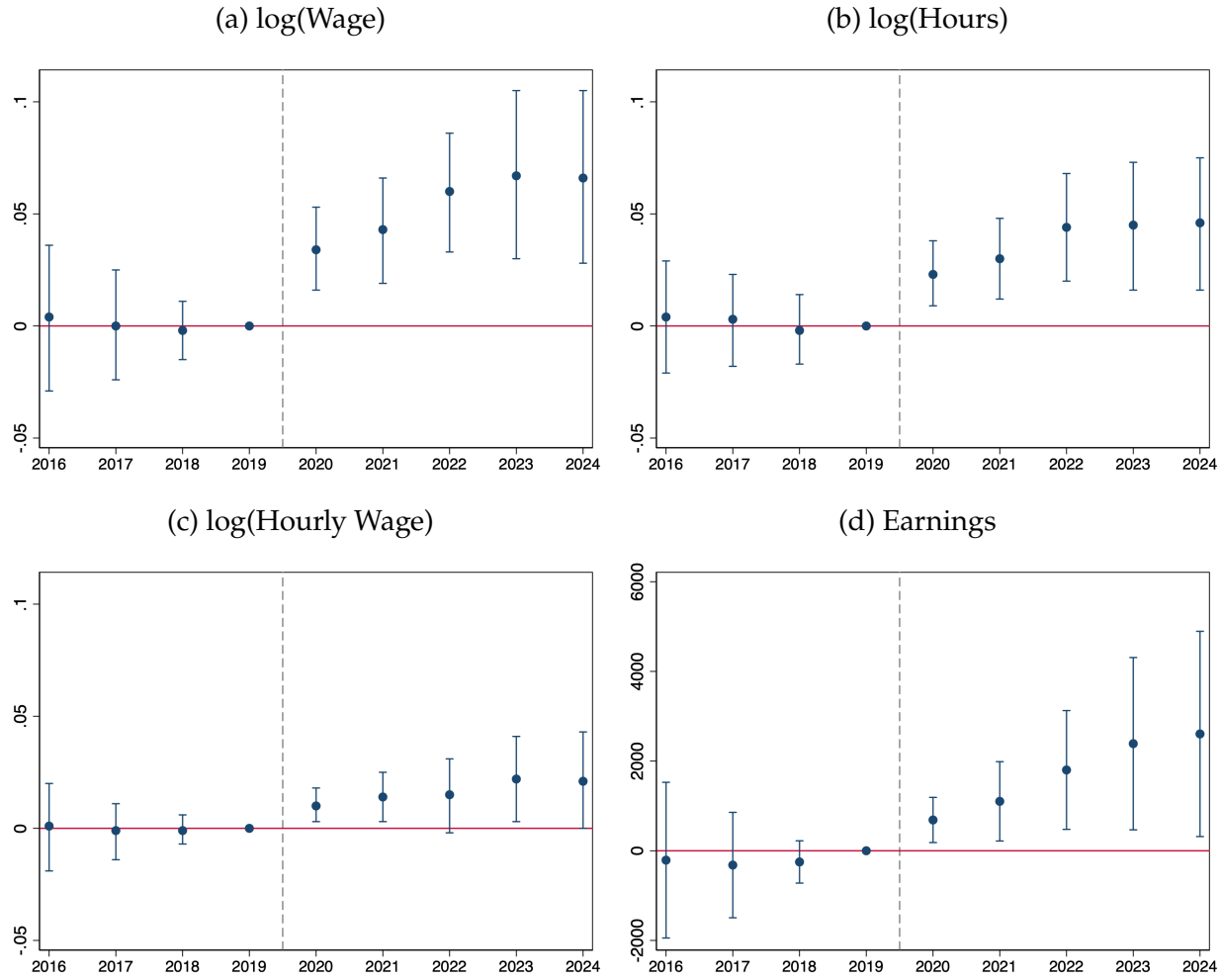


(b) Hybrid Teleworking



Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (1), where we compare teleworking rates of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020). The specification controls for 3-digit occupation fixed effects and firm size bins × age class × industry × gender × year fixed effects. Standard errors are clustered at the occupation level. The dependent variables are a dummy equal to one if the employee works only from home (Panel a) and a dummy equal to one if the employee works partially from home (Panel b).

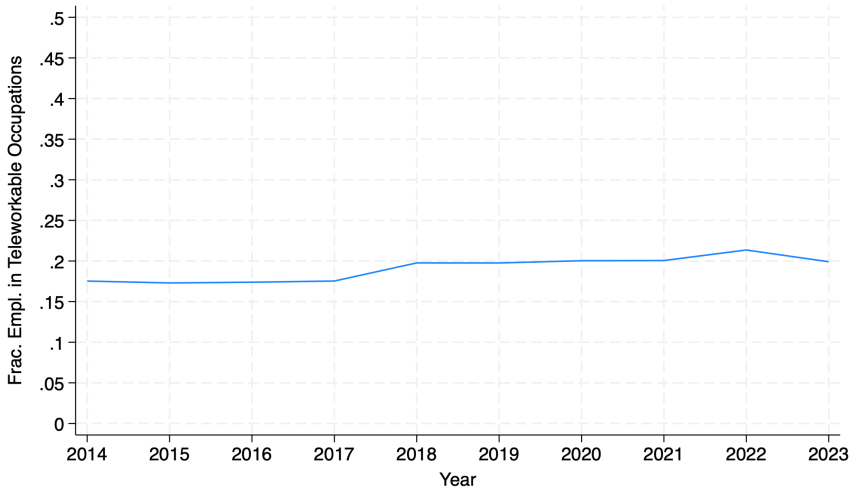
Figure 2. Teleworkability and Labor Market Outcomes



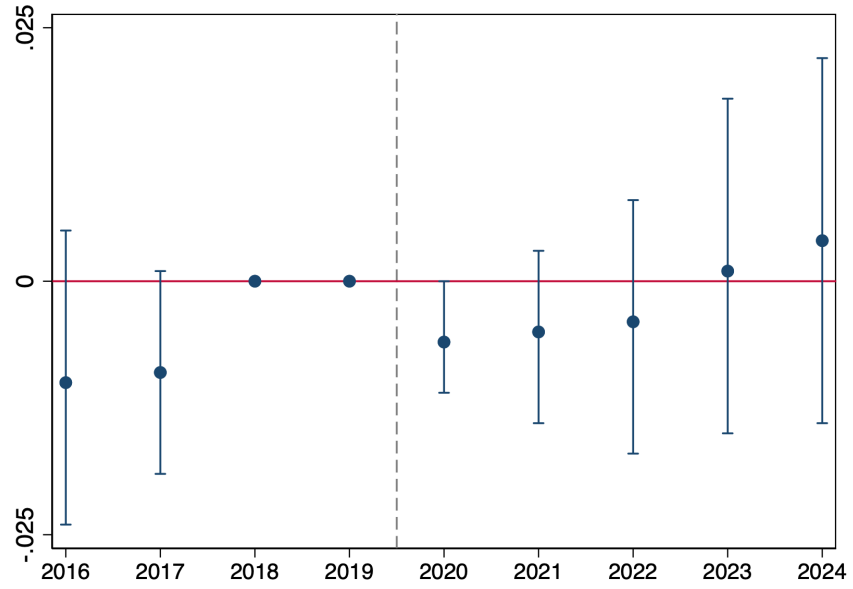
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variables are the logarithm of the worker's wage (Panel a); the logarithm of hours worked (Panel b); the natural logarithm of the hourly wage (Panel c); and total earnings (Panel d).

Figure 3. Teleworkability and Employment

(a) Employment share

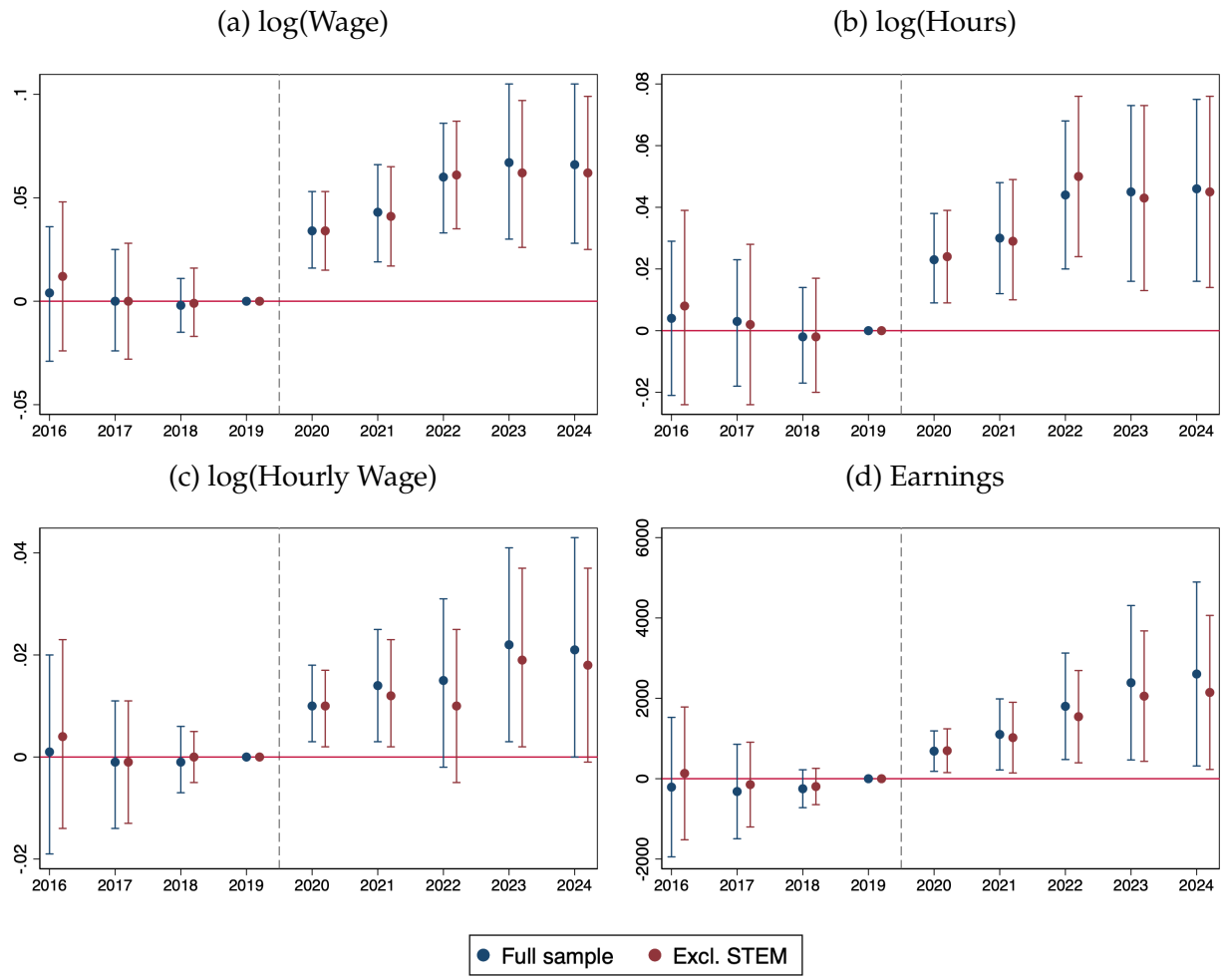


(b) Employment



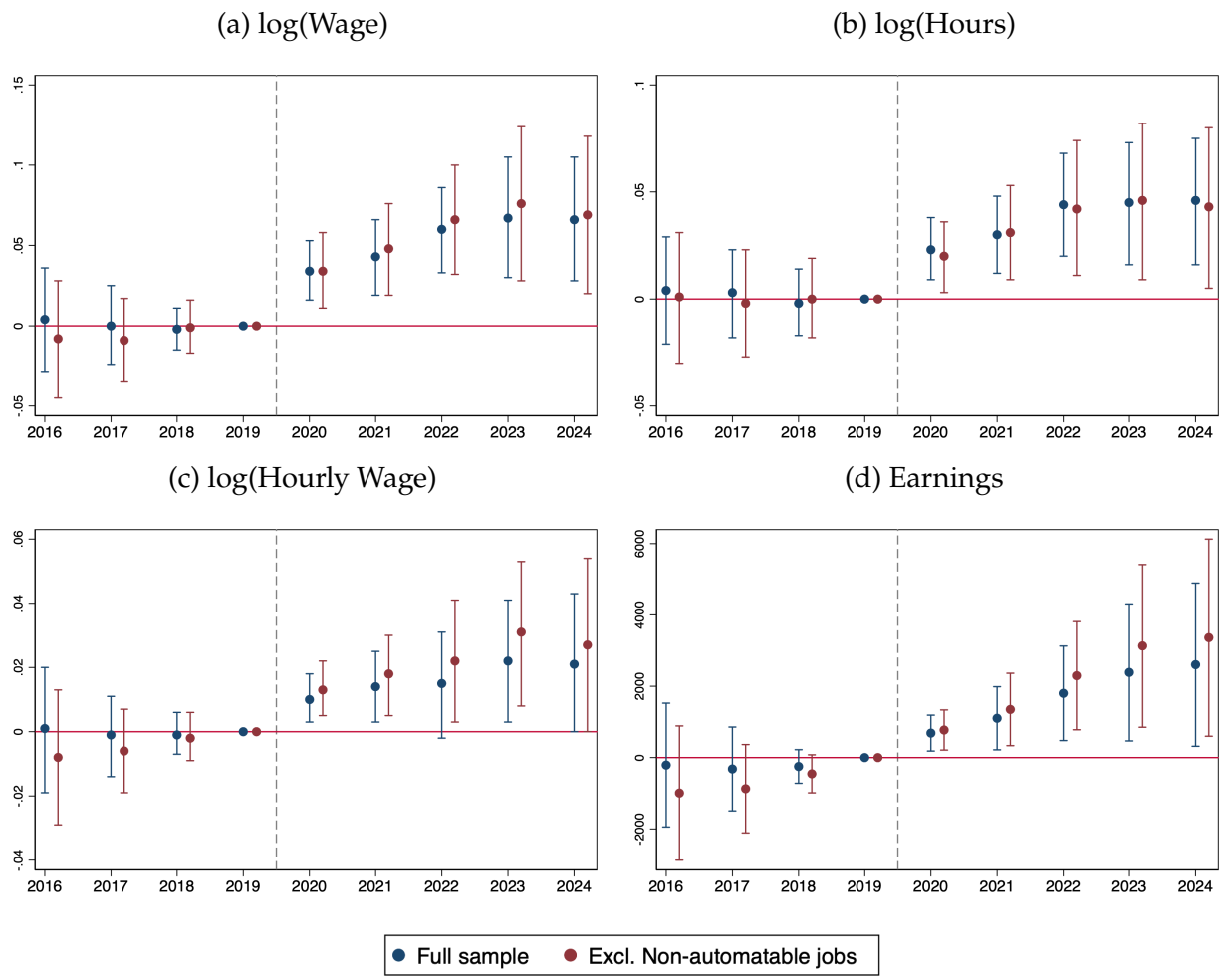
Notes: Panel a of this figure displays the fraction of employees in telworkable occupations in the EBB and NEA surveys for the years 2014–2023. The teleworkability classification is from Dingel and Neiman (2020). Panel b displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The sample is obtained after performing the matching procedure described in Section 3.2. We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variable is a dummy equal to one if the worker is employed.

Figure 4. Excluding STEM Workers



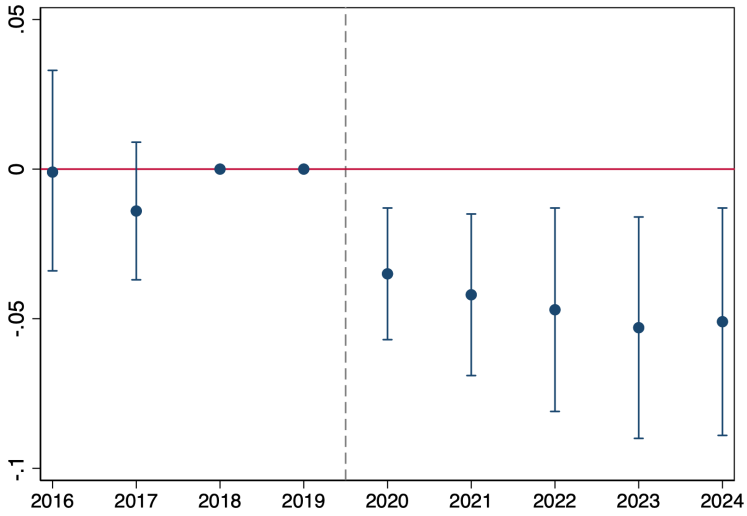
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. We plot coefficients estimated on the full sample (in blue) and on the subsample of workers for which we know the educational attainment and that do not have a STEM degree (in red). We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variables are the logarithm of the worker's wage (Panel a); the logarithm of hours worked (Panel b); the natural logarithm of the hourly wage (Panel c); and total earnings (Panel c).

Figure 5. Excluding Workers with Non-automatable Jobs



Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. We plot coefficients estimated on the full sample (in blue) and on the subsample of workers with nonzero exposure to automation (in red). We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variables are the logarithm of the worker's wage (Panel a); the logarithm of hours worked (Panel b); the natural logarithm of the hourly wage (Panel c); and total earnings (Panel c).

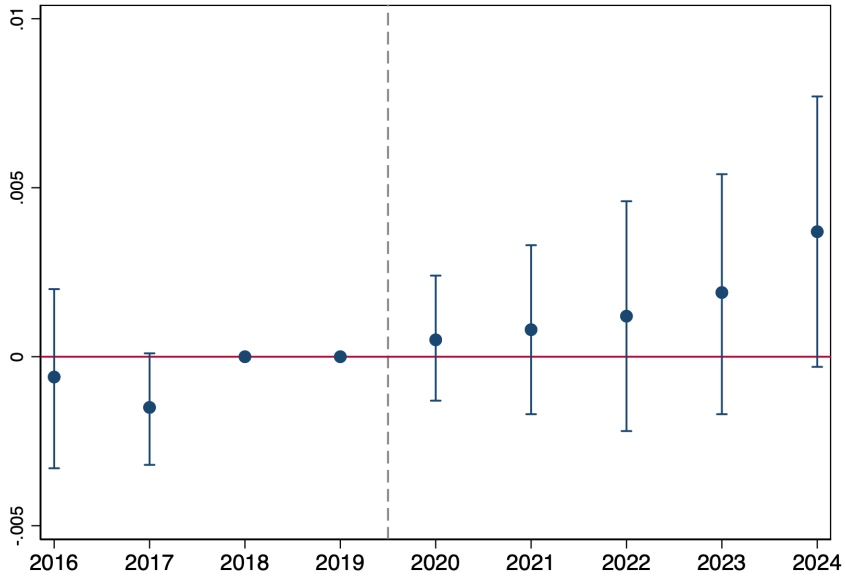
Figure 6. Teleworkability and Firm Retention



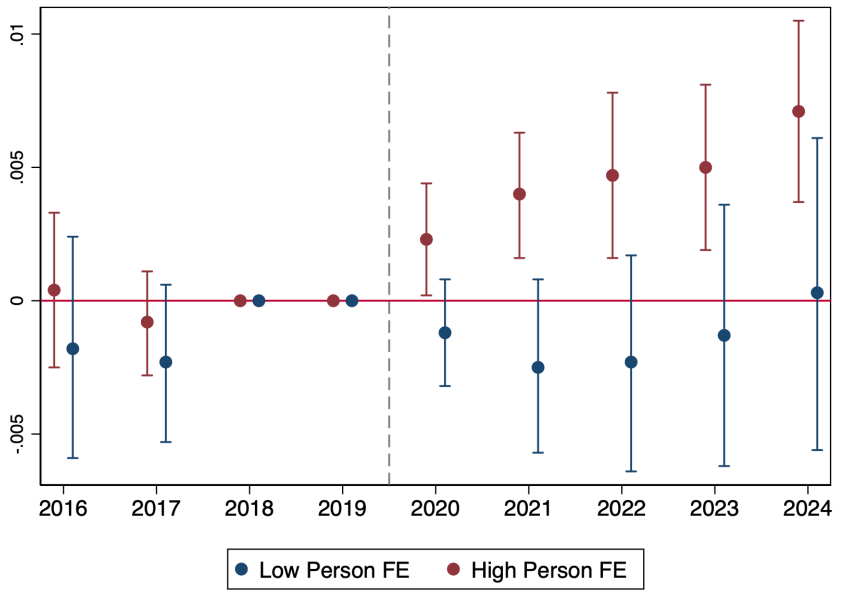
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variable is a dummy equal to one if the worker is employed with their 2019 employer.

Figure 7. Teleworkability and Firm Wage Premia

(a) Full Sample

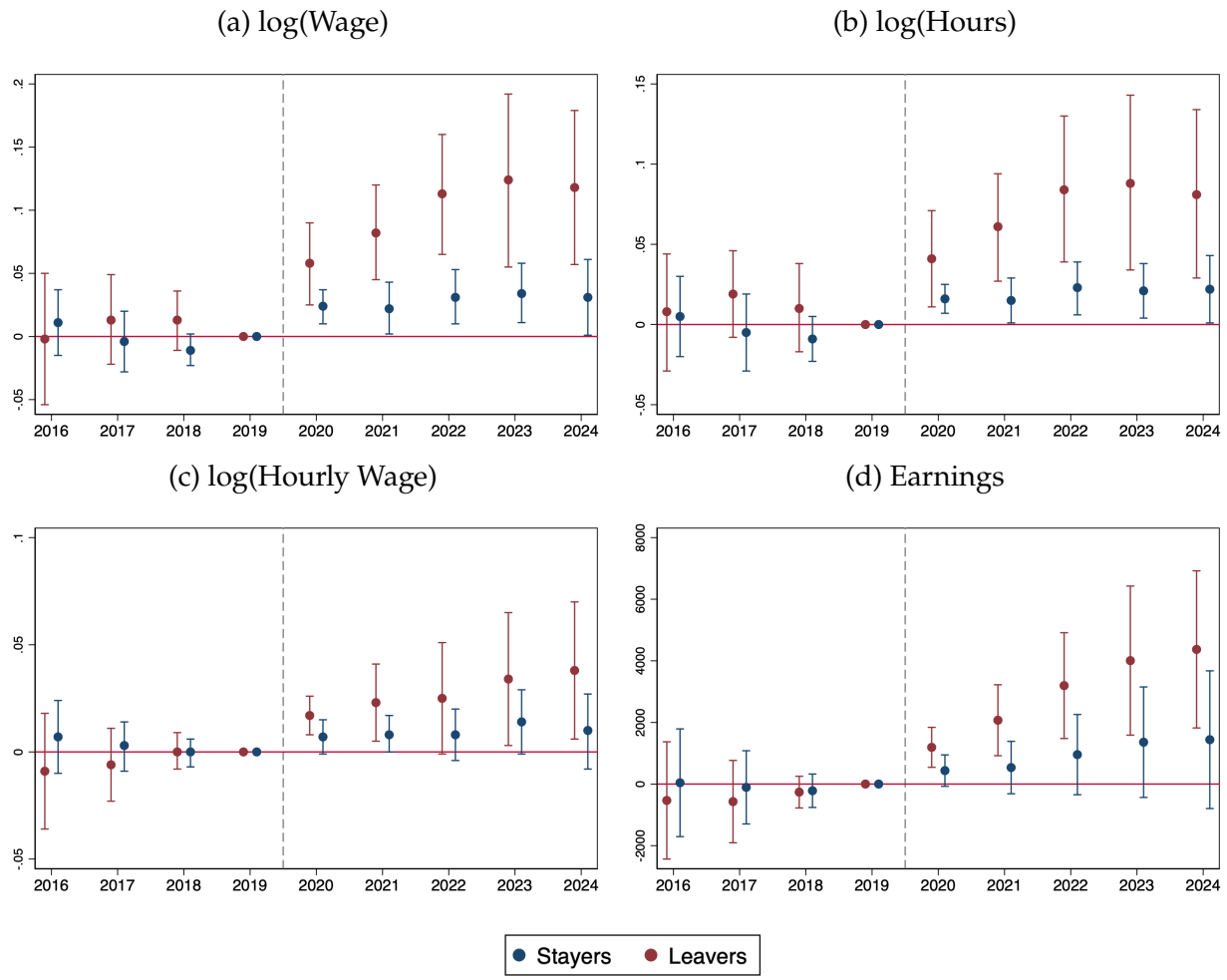


(b) High- vs Low-Skill Workers



Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variable is the firm wage premium, estimated over the CBS sample in the period 2010–2019. The coefficients displayed in Panel (a) are estimated over the full sample. In Panel (b) we distinguish between high- and low-skill workers (in red and blue, respectively), where high skill are workers with a worker fixed effect above the sample median and low-skill are workers with a workers fixed effect below the sample median.

Figure 8. Stayers and Leavers



Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. We plot coefficients estimated on the subsample of stayers (in blue) and on the subsample of leavers (in red). Stayers are the workers who are employed with their 2019 employer throughout the period 2020–2024, whereas leavers are those who eventually move to a new employer. We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variables are the logarithm of the worker's wage (Panel a); the logarithm of hours worked (Panel b); the natural logarithm of the hourly wage (Panel c); and total earnings (Panel c).

Tables

Table 1. Teleworkable vs. Non-Teleworkable Jobs: Descriptive Statistics, 2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample			Matched Sample		
	Non-TW job	TW job	Δ	Non-TW job	TW job	Δ
Targeted						
Log(Wage)	10.281	10.568	0.287	10.439	10.404	-0.034
	(0.089)	(0,098)	(0.131)	(0.089)	(0.120)	(0.147)
Log(Wage)$_{t-2}$	10.206	10.501	0.294	10.369	10.331	-0.038
	(0.096)	(0.097)	(0.135)	(0.093)	(0.125)	(0.153)
High Tenure	0.585	0.622	0.037	0.582	0.582	0.000
	(0.016)	(0.027)	(0.031)	(0.015)	(0.017)	(0.022)
Age	45.608	44.797	-0.811	45.640	45.789	0.149
	(0.364)	(0.634)	(0.718)	(0,420)	(0.536)	(0,670)
Male	0.544	0.415	-0.128	0.520	0.520	-0.000
	(0.092)	(0.101)	(0.135)	(0.080)	(0.106)	(0.131)
Log(Firm Size)	5.778	5.521	-0.257	5.616	5.626	0.010
	(0.261)	(0.174)	(0.311)	(0.190)	(0.267)	(0.322)
Not Targeted						
Log(Hourly Wage)	2.978	3.250	0.273	3.079	3.123	0.044
	(0.043)	(0.057)	(0.070)	(0.045)	(0.057)	(0.072)
Log(Hourly Wage)$_{t-2}$	2.929	3.206	0.277	3.033	3.076	0.043
	(0.044)	(0.056)	(0.070)	(0.046)	(0.057)	(0.072)
Log(Hours)	7.305	7.319	0.015	7.358	7.281	-0.076
	(0.064)	(0.051)	(0.081)	(0.058)	(0.069)	(0.088)
Earnings	35271.438	47411.070	12139.632	41172.570	40524.297	-648.271
	(2460.517)	(4882.152)	(5357.080)	(2990.542)	(4375.945)	(5207.631)
Permanent Contract	0.816	0.855	0.039	0.829	0.814	-0.015
	(0.018)	(0.019)	(0.026)	(0.015)	(0.023)	(0.028)
Observations	25,237	22,016	47,253	6,098	6,098	12,196

Notes: Descriptive statistics for workers in teleworkable ("TW") and non-teleworkable ("Non-TW") jobs. The teleworkability classification is obtained from Dingel and Neiman (2020). Statistics are reported for the full sample (Columns 1-3) and the matched sample of treated and control workers resulting from the matching algorithm described in Section 3 (Column 4-6). Columns (3) and (6) report estimated differences between the two groups. The first panel (*Targeted*) refers to variables included in the propensity score matching, while the second panel (*Not Targeted*) considers variables excluded from the matching algorithm. Standard deviations are in parentheses.

Table 2. Teleworkability and Teleworking

	(1)	(2)
	Full Teleworking	Hybrid Teleworking
Contemporaneous effect	0.152	0.146
	(0.032)	(0.024)
Long-run effect	0.065	0.118
	(0.017)	(0.023)
Observations	244,087	244,087
R^2	0.182	0.452
Mean outcome	0.012	0.105
Standard deviation	0.110	0.306

Notes: This table shows the contemporaneous (2020) and long-run (2023) event-study coefficients obtained after estimating Equation (1), where we compare teleworking rates of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020). The specification controls for 3-digit occupation fixed effects and firm size bins × age class × industry × gender × year fixed effects. The dependent variables are a dummy equal to one if the employee works only from home (Column 1) and a dummy equal to one if the employee works partially from home (Column 2). Standard errors, clustered at the occupation level, are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 3. Teleworkability and Labor Market Outcomes

	(1)	(2)	(3)	(4)
	log(Wage)	log(Hours)	log(Hourly Wage)	Earnings
Contemporaneous effect	0.034	0.023	0.01	686.677
	(0.009)***	(0.007)***	(0.004)***	(252.349)***
Long-run effect	0.066	0.046	0.021	2,605.589
	(0.019)***	(0.015)***	(0.011)**	(1147.2)**
Observations	105,834	105,840	105,834	109,746
R^2	0.817	0.689	0.915	0.851
Mean outcome	10.343	7.316	3.026	38,252.805
Standard deviation	0.688	0.470	0.379	22,576.178

Notes: This table shows the contemporaneous (2020) and long-run (2024) event-study coefficients obtained after estimating Equation (1), where we compare teleworking rates of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. The specification controls for worker fixed effects and year fixed effects. The dependent variables are the logarithm of the worker's wage (Column 1); the logarithm of hours worked (Column 2); the natural logarithm of the hourly wage (Column 3); and total earnings (Column 4). Standard errors, clustered at the occupation level, are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 4. Teleworkability and Labor Mobility

	(1)	(2)	(3)	(4)
	Firm	Firm Wage Premia		
	Retention	Full Sample	Low Person FE	High Person FE
Contemporaneous effect	-0.035	0.001	-0.001	0.002
	(0.011)***	(0.001)	(0.001)	(0.001)**
Long-run effect	-0.051	0.0037	0.000	0.007
	(0.019)***	(0.002)*	(0.003)	(0.002)***
Observations	105,904	101,643	50,454	51,089
R^2	0.474	0.857	0.824	0.891
Mean outcome	0.907	0.016	0.009	0.024
Standard deviation	0.291	0.107	0.107	0.107

Notes: This table shows the contemporaneous (2020) and long-run (2024) event-study coefficients obtained after estimating Equation (1), where we compare teleworking rates of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. The specification controls for worker fixed effects and year fixed effects. The dependent variables are a dummy variable equal to one if the worker is employed with their 2019 employer (Column 1); the firm wage premium, estimated over the CBS sample in the period 2010–2019 using AKM regressions (Columns 2-4). In Column 2, the regression is estimated over the full sample; in Columns 3-4 we distinguish between low- and high-fixed effects workers (Column 3 and 4, respectively), where high-fixed effect workers have an estimated individual AKM fixed effect above the sample median, and low-fixed effect workers have an estimated individual AKM fixed effect below the sample median. Standard errors, clustered at the occupation level, are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 5. Teleworkability and Labor Market Outcomes: Stayer vs. Leavers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Wage)		log(Hours)		log(Hourly Wage)		Earnings	
	Stay	Leave	Stay	Leave	Stay	Leave	Stay	Leave
Contemporaneous effect	0.023	0.059	0.015	0.042	0.007	0.017	417.336	1,217.778
	(0.007)	(0.016)	(0.005)	(0.014)	(0.004)	(0.005)	(256.431)	(318.102)
Long-run effect	0.031	0.121	0.022	0.084	0.010	0.038	1,413.516	4,454.690
	(0.015)	(0.031)	(0.010)	(0.026)	(0.009)	(0.016)	(1,117.150)	(1,251.239)
Observations	67,476	38,382	67,481	38,384	67,476	38,382	70,299	39,465
R^2	0.849	0.659	0.637	0.395	0.476	0.557	0.863	0.452
Mean outcome	10.433	10.164	7.357	7.234	3.075	2.931	40,699.691	33,463.457
Standard deviation	0.640	0.744	0.430	0.532	0.367	0.383	22,763.502	21,411.674

Notes: This table shows the contemporaneous (2020) and long-run (2024) event-study coefficients obtained after estimating Equation (1), where we compare teleworking rates of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. The specification controls for worker fixed effects and year fixed effects. The dependent variables are the logarithm of the worker's wage (Columns 1-2); the logarithm of hours worked (Columns 3-4); the natural logarithm of the hourly wage (Columns 5-6); and total earnings (Columns 7-8). Each regression is estimated separately on the subsample of stayers (odd columns) and on the subsample of leavers (even columns). Stayers are the workers who are employed with their 2019 employer throughout the period 2020–2024, whereas leavers are those who eventually move to a new employer. Standard errors, clustered at the occupation level, are in parentheses. * p<0.10, ** p<0.05, *** p<0.01.