TRAILS

Enabling Data Analytics for Actions
Tackling Skills Shortages & Mismatch

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ACRONYMS

Acronym	Explanation
ISCO	International Standard Classification of Occupations
ISCED	International Standard Classification of Education
CBS	Centraal Bureau voor de Statistiek
STEM	Science, technology, engineering and mathematics
WFH	Work from Home
UNESCO	United Nations Educational, Scientific and Cultural Organization
OECD	Organisation for Economic Co-operation and Development
EBB	Enquête Beroepsbevolking
NEA	Nationale Enquête Arbeidsomstandigheden
NACE	Nationale Enquête Arbeidsomstandigheden

EXECUTIVE SUMMARY

The expansion of work-from-home (WFH) arrangements following the COVID-19 pandemic represents one of the most profound and persistent shifts in labor markets in recent decades. In the United States, the share of workdays performed from home increased fourfold between 2019 and 2023, with comparable—though somewhat smaller—changes observed across European countries. This structural change has spurred a growing literature examining WFH as a job amenity negotiated between firms and workers, with implications for productivity, firm organization, and worker welfare. However, there is still limited causal evidence on how the widespread availability of WFH has reshaped workers' career paths, job mobility, and long-term earnings dynamics.

Chapter 1 of this deliverable analyzes the career effects of WFH by focusing on access to teleworking opportunities. The working hypothesis is that access to WFH potentially expands workers' choice sets by widening the relevant labor market, allowing them to search for, and transition to, better-matched jobs.

To perform our analysis, we combine administrative matched employer–employee data with repeated cross-section survey information on WFH take-up for the Netherlands, the European country with the highest incidence of remote work. A key feature of the data is the availability of detailed occupational classifications, which we map into a measure of teleworkability using the index developed by Dingel and Neiman (2020). This classification captures the feasibility of working from home based on occupational tasks and required technologies and is fixed prior to the pandemic. We further leverage the sudden adoption of WFH technologies induced by the COVID-19 pandemic as a source of variation in the availability of teleworking opportunities. We note that this shock disproportionately benefits occupations that were already more amenable to remote work before the pandemic, and exploit this heterogeneity to identify the causal effects of expanded WFH availability across occupations in a difference-in-differences setting.

We first document that pre-pandemic teleworkability strongly predicts post-pandemic WFH adoption. Occupations classified as teleworkable experienced a large and persistent increase in WFH rates after 2019, particularly in hybrid arrangements combining on-site and remote work. Compared to non-teleworkable occupations, WFH rates in teleworkable jobs rose by roughly 15 percentage points in 2020, with only limited reversion over time. This finding validates our empirical strategy and confirms that workers in teleworkable occupations were substantially more likely to be "treated" by the post-pandemic diffusion of WFH.

We then turn to the main analysis of workers' career trajectories using longitudinal administrative data. We estimate difference-in-differences models that compare workers employed in teleworkable occupations in 2019 to otherwise similar workers in non-teleworkable occupations. To ensure comparability across groups, each treated worker is matched to a statistical "twin" based on pre-pandemic characteristics, including wages, tenure, industry, firm size, age, and gender. Our analysis focuses on a balanced panel of approximately 12,200 workers observed up to four years after the onset of the pandemic.

The results reveal sizeable and persistent earnings gains for workers in teleworkable occupations. Four years after the pandemic, treated workers earn almost 7 log points more than their matched counterparts in non-teleworkable jobs. These gains are primarily driven by an increase in hours worked, but we also find meaningful and statistically significant improvements in hourly wages. Importantly, we detect no differential effects on overall employment probabilities, implying that, during the pandemic, workers in non-teleworkable occupations did not experience larger job losses than their counterparts in teleworkable occupations. This result ensures that the positive earnings effects we detect are not driven by "scarring effects" of unemployment affecting the control group.

To dig deeper into the mechanisms underlying these earnings gains, we investigate job mobility and labor market matching. While employment rates remain similar across groups, workers in teleworkable occupations are significantly less likely to remain with their pre-pandemic employer. Further analysis shows that the earnings gains are mostly driven by workers who switch employers after 2019. Using firm-level wage premia and workers' ability, estimated from pre-pandemic data following Abowd et al. (1999), we show that high-ability workers in teleworkable occupations are more likely to transition to higher-paying firms. These findings suggest that expanded access to WFH widened labor markets, facilitating assortative matching between high-wage workers and high-wage firms.

The specific focus on Netherlands in Chapter 1 allows us to combine rich matched employer-employee data with survey-level information on WFH. In Chapter 2 of this deliverable, we extend the analysis to other European countries (France, Germany, Italy, and Spain) and provide suggestive evidence that the results of Chapter 1 are generalizable to other settings. We show that, across these economies, the “teleworkability” classification developed in Dingel and Neiman (2020) predicts a higher probability of working away from the employer’s facilities after the pandemic, as reported in the European Skills and Jobs Survey (ESJS) **(**Cedefop, 2021)**.** Importantly, this finding remains robust in a formal regression framework, where we account for heterogeneity with respect to countries, industry, education, and income. This empirical analysis demonstrates that the link between teleworkability and working from home is not unique to the Netherlands but reflects broader labor market characteristics. While the pandemic has substantially transformed the labor market by expanding teleworking opportunities, access to work-from-home remains closely tied to workers’ occupations.

The results emerging from this deliverable have several important policy implications. First, they suggest that WFH should be viewed not only as a workplace flexibility or work–life balance tool, but also as a labor market infrastructure that affects mobility, matching efficiency, and long-term earnings growth. Policies that support the diffusion of remote work technologies—such as investments in digital infrastructure, broadband access, and remote collaboration tools—may yield productivity and welfare gains by enhancing workers’ ability to access better job matches.

Second, the uneven benefits across worker types highlight the risk of increasing labor market inequality. While high-ability workers in teleworkable occupations appear to benefit substantially from expanded WFH opportunities, lower-skilled workers do not experience comparable gains. This underscores the importance of complementary policies, including training and reskilling programs, that enable a broader set of workers to take advantage of remote and hybrid work opportunities.

Overall, this deliverable provides new causal evidence that the post-pandemic expansion of WFH has reshaped workers’ careers primarily by increasing job mobility and improving labor market matching, with important consequences for earnings dynamics.

Purpose of the Deliverable

This report examines the impact of the sudden adoption of teleworking arrangements during the COVID-19 pandemic on the subsequent labour market outcomes of affected workers. Specifically, using matched employer–employee administrative data from the Netherlands combined with survey data providing detailed information on occupations and work-from-home (WFH) use, Chapter 1 aims to (i) assess whether the pandemic led to a persistent increase in the prevalence of teleworking arrangements; (ii) analyse the consequences of teleworking availability for workers' careers—including earnings, employment, hours worked, and sorting; and (iii) test whether expanded access to WFH improves match quality in the labour market. Chapter 2 extends the analysis to other large European economies (France, Germany, Italy, and Spain) to provide suggestive evidence that results for the Netherlands are likely generalizable to other settings.

Relation with other Deliverables and Tasks

This study directly contributes to the objectives of the TRAILS project by shedding light on how the expanded availability of work-from-home (WFH) arrangements has reshaped workers' career trajectories and labour market dynamics. By examining WFH as a technology that relaxes geographical constraints and alters job search, mobility, and matching processes, the analysis speaks to TRAILS' overarching aim of understanding the evolving structure of labour markets and the conditions required for skills to effectively match current and future labour demand. The study highlights the mediating role of digital technologies in fostering labour market resilience, while also pointing to heterogeneity in outcomes across worker skill levels. Methodologically, the use of rich administrative and survey data aligns with TRAILS' ambition to use state-of-the-art datasets and empirical tools capable of addressing causal questions. More broadly, the findings inform TRAILS' integrated analytical framework by linking technological adoption, behavioural responses, and institutional conditions to labour market matching and career development, thereby providing evidence relevant for the design of coherent policy interventions in line with the European Skills Agenda.

This deliverable is related to deliverable D1.1, which presents a review of the recent literature on skill mismatch. Specifically, the deliverable D1.1 informs and motivates the empirical tests conducted in the section on assortative matching between workers and firms: Section 2 of deliverable D1.1 identifies search frictions and/or imperfect information about workers' skills and job tasks as the main drivers of labor mismatch, and Section 5.1.1 refers to geographical constraints and relocation costs as the main source of search costs. Furthermore, it hypothesizes that the introduction of work-from-home arrangements improves skill matching by substantially reducing geographical frictions and relocation costs.

This report is closely related to Deliverable D4.3, which aims to quantify the effect of skill match quality on firms' ability to respond to recent shocks, including the COVID-19 pandemic, major technological innovations, and sudden spikes in energy prices. It is also connected to Deliverable D3.1, which, among other issues, examines the evolution of educational mismatch over time and its association with the adoption of work-from-home (WFH) arrangements. Finally, this report relates to—and is intended to help motivate—the analyses developed in Deliverable D4.4, which more directly investigates the factors that may contribute to a reduction in skill mismatch.

Structure of the Document

The document comprises two chapters. Chapter 1 begins with an introduction that summarizes the main findings of the papers, Section 2 presents the data and Section 3 presents the econometric methodology. Section 4 discusses and interprets the empirical results, and Section 5 makes concluding remarks highlighting policy implications. Chapter 2 also begins with a brief introduction, Section 2 summarizes work-from-home patterns across Europe, Section 3 presents the empirical analysis, and Section 4 concludes by taking stock of results and their implications.

1. Educational Mismatch in Europe: Incidence, Determinants and the Impact of an Increase in Remote Working

1.1 Introduction

The rise of work-from-home (WFH) has been among the most dramatic shifts that 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). A key feature of the data is the availability of detailed occupational categories, which we classify according to the feasibility of working from home using the teleworkability classification introduced by Dingel and Neiman (2020). This approach assigns a teleworkability index to each occupation based on job tasks and required technologies. Indeed, we focus on the effect of having access to the possibility of teleworking, as opposed to the realized practice of working from home.

We begin by assessing whether this measure of teleworkability predicts the adoption of WFH arrangements in the post-pandemic period. In this context, the pandemic can be viewed as a shock that suddenly accelerated the diffusion of WFH technologies. Our objective is to test whether occupations that were ex ante more teleworkable subsequently adopted WFH arrangements more frequently and more persistently than non-teleworkable occupations, implying that workers in these occupations were more likely to receive a teleworking "treatment". 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, 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 increase 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 propensity 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 the career paths of 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 also detect insignificant effects on overall employment probabilities—

implying an overall increase in total labor earnings (or 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 to retain 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 the estimated 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 pre-pandemic 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 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.

1.2 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 more in detail below, and how we combine them to obtain our final dataset.

1.2.1 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' wage, 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 allows us to identify both the educational attainment (elementary school, high school, vocational school, bachelor or master 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.

1.2.2 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.

Figure 1 plots the fraction of workers who claim to work partially or fully from home in the 2014-2023 waves of the NEA survey. There is a clear spike in 2020, which jumps to roughly 50%, and does not fade away in the subsequent years. As shown in Figure 29, where we focus on full-time work-from-home, teleworking exhibits a jump and then a partial reversal in the subsequent years.

Moreover, in Figures 30 through 33 in the Appendix, we report additional statistics on the fraction of employees who engage in partial or full teleworking in different categories of age, industry, occupation, and firm size. We find that there is a clear association between work-from-home and firm size, as measured by its employment. Moreover, we document a negative relationship between work-from-home and age, suggesting that the "digital divide" across generations may represent a significant impediment for older individuals in their ability to adopt flexible working arrangements. We also show that work-from-home is the highest in industries such as energy, ICT, and real estate, and lowest in trade and agriculture.

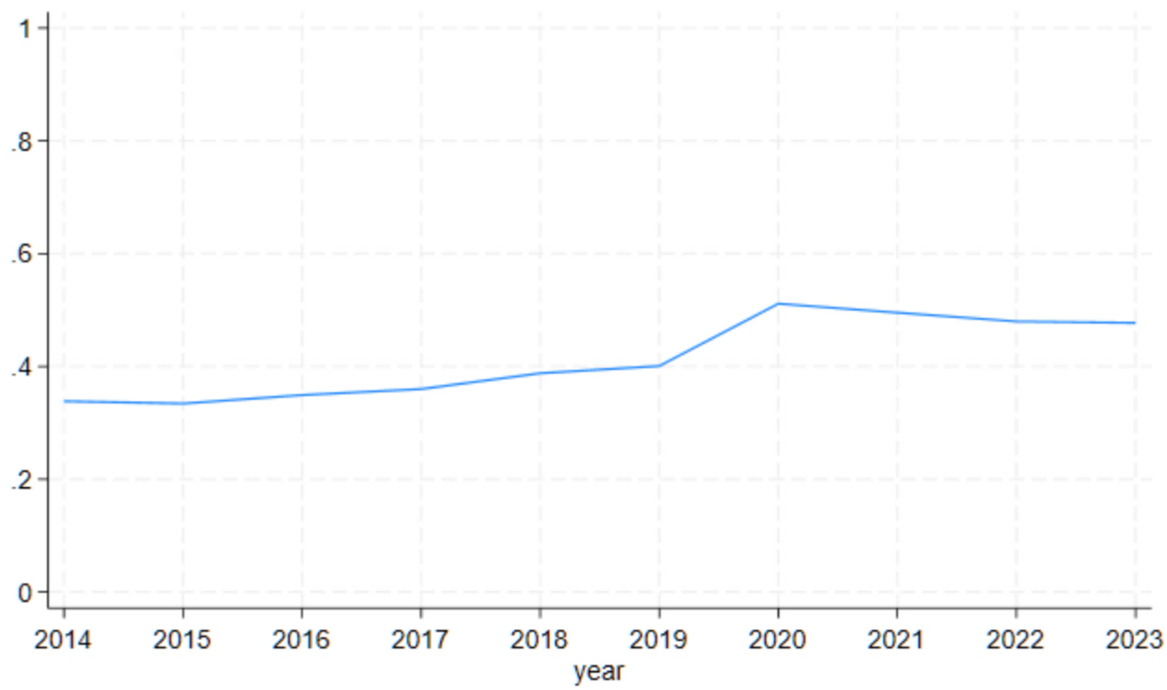
This heterogeneity motivates the importance of the matching strategy that we describe below. Indeed, we will compare postpandemic outcomes of workers employed in the same industry, with

[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.

a similar age and employed in firms of comparable size, therefore ruling out the risk that these observable characteristics could drive differences in outcomes.

Finally, Figure 33 shows that takeup of work-from-home is largely concentrated in four occupations, namely armed forces, managers, scientists, and technicians. These occupations may be characterized by different characteristics (earnings profile, unemployment risk, skill level, exposure to automation risk, etc.). We discuss in the next sections how we tackle these additional confounding risks.

Figure 1: Trends in Teleworking



Notes: This figure displays the fraction of workers in the NEA surveys 2014-2023 who claim to work fully or partially from home.

1.2.3 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. 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. 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 is 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 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 a 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.

1.3 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.

1.3.1 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:

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

$i, j,$ 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 $s \times$ age bin $a \times$ industry $k \times$ gender $g \times$ year t fixed effects. 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.

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

1.3.2 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 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. In Table 2, where we list descriptive statistics for variables *not* used in the matching algorithm, we also find important differences in hourly wages and earnings.

Table 1: Teleworkable vs. Non-Teleworkable Jobs: Descriptive Statistics, Full Sample – Targeted Moments

	(1)	(2)	(3)
	Non-TW job	TW job	Δ
Log(Wage)	10.281	10.568	0.287
	(0.089)	(0.098)	(0.131)
Log(Wage)$_{t-2}$	10.206	10.501	0.294
	(0.096)	(0.097)	(0.135)
High Tenure	0.585	0.622	0.037
	(0.016)	(0.027)	(0.031)
Age	45.608	44.797	-0.811
	(0.364)	(0.634)	(0.718)
Male	0.544	0.415	-0.128
	(0.092)	(0.101)	(0.135)
Log(Firm Size)	5.778	5.521	-0.257
	(0.261)	(0.174)	(0.311)
Observations	25,237	22,016	47,253

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 for the moments used in the propensity score algorithm. Column (3) reports estimated differences between the two groups. Standard deviations are in parentheses.

Table 2: Teleworkable vs. Non-Teleworkable Jobs: Descriptive Statistics, Full Sample – Non-Targeted Moments

	(1)	(2)	(3)
	Non-TW job	TW job	Δ
Log(Hourly Wage)	2.978	3.250	0.273
	(0.043)	(0.057)	(0.070)
Log(Hourly Wage)$_{t-2}$	2.929	3.206	0.277
	(0.044)	(0.056)	(0.070)
Log(Hours)	7.305	7.319	0.015
	(0.064)	(0.051)	(0.081)
Earnings	35271.438	47411.070	12139.632
	(2460.517)	(4882.152)	(5537.080)
Permanent Contract	0.816	0.855	0.039
	(0.018)	(0.019)	(0.026)
Observations	25,237	22,016	47,253

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 for moments not used in the propensity score algorithm. Column (3) reports estimated differences between the two groups. Standard deviations are in parentheses.

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 continuous variables at the 1 percent level. We fit this model for each gender × tenure at the firm × industry cell, meaning that we match *exactly* on these categorical characteristics. (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.) Treated workers are matched with control workers with 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.

Table 3 reports 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, Table 4 shows that 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.

Table 3: Teleworkable vs. Non-Teleworkable Jobs: Descriptive Statistics, Matched Sample – Targeted Moments

	(1)	(2)	(3)
	Non-TW job	TW job	Δ
Log(Wage)	10.439	10.404	-0.034
	(0.089)	(0.120)	(0.147)
Log(Wage)$_{t-2}$	10.369	10.331	-0.038
	(0.093)	(0.125)	(0.153)
High Tenure	0.582	0.582	0.000
	(0.015)	(0.017)	(0.022)
Age	45.640	45.789	0.149
	(0.420)	(0.536)	(0.670)
Male	0.520	0.520	-0.000
	(0.081)	(0.106)	(0.131)

Log(Firm Size)	5.616	5.626	0.010
	(0.190)	(0.267)	(0.322)
Observations	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 matched sample of treated and control workers resulting from the matching algorithm described in Section 3. Column (6) reports estimated differences between the two groups. The table includes variables included in the matching algorithm. Standard deviations are in parentheses.

Table 4: Teleworkable vs. Non-Teleworkable Jobs: Descriptive Statistics, Matched Sample – Non-Targeted Moments

	(1)	(2)	(3)
	Non-TW job	TW job	Δ
Log(Hourly Wage)	3.079	3.123	0.044
	(0.045)	(0.057)	(0.072)
Log(Hourly Wage)$_{t-2}$	3.033	3.076	0.043
	(0.046)	(0.057)	(0.072)
Log(Hours)	7.358	7.281	-0.076
	(0.058)	(0.069)	(0.088)
Earnings	41172.570	40524.297	-648.271
	(2990.542)	(4375.945)	(5207.631)
Permanent Contract	0.829	0.814	-0.015
	(0.015)	(0.023)	(0.028)
Observations	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 matched sample of treated and control workers resulting from the matching algorithm described in Section 3. Column (6) reports estimated differences between the two groups.

The table includes variables excluded from the matching algorithm. Standard deviations are in parentheses.

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

$$y_{it} = \sum_{\tau=2016(\neq 2019)}^{2024} \beta_\tau \times 1(t=\tau) \times Teleworkability_{j(i)}^{2019} + \alpha_i + \gamma_t + \varepsilon_{it} \qquad (2)$$

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 nonteleworkable 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_{it} 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-job transitions, and wage premia. We postpone the definitions of the relevant outcome variables for these tests to Sections 4.4 and 4.5.

1.4 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.

1.4.1 Worker-Level Design

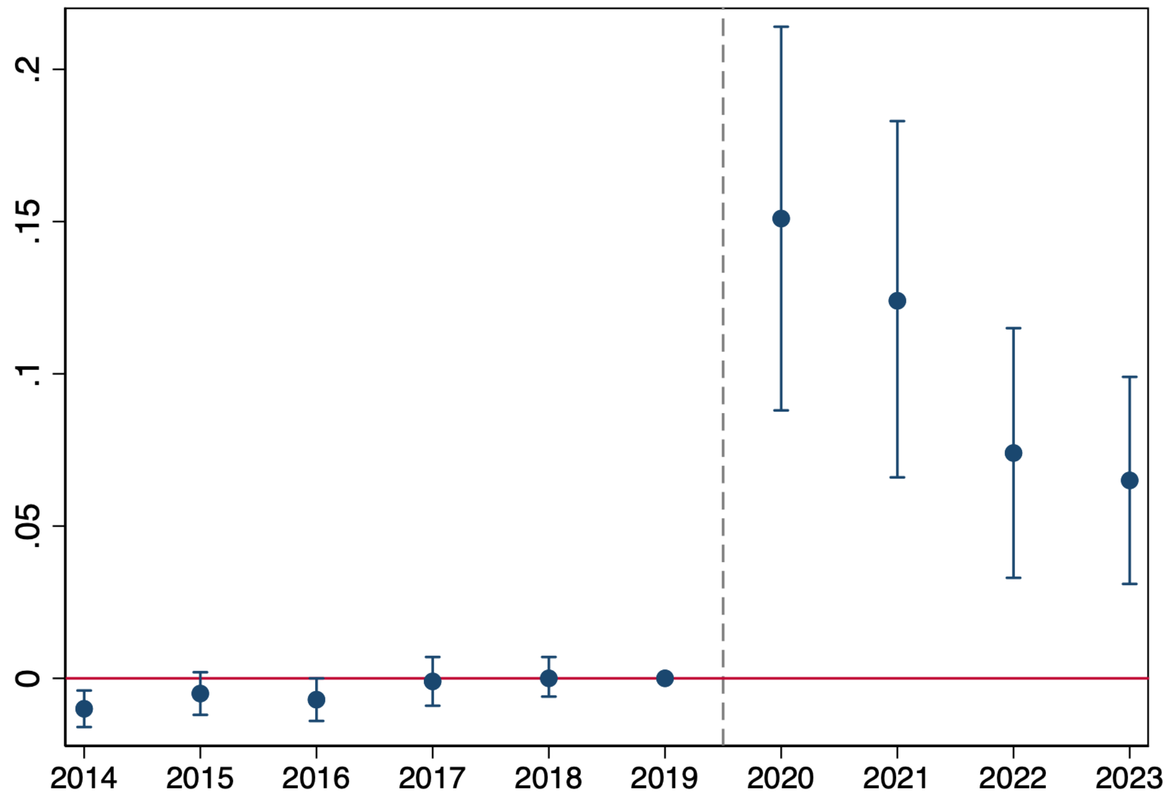
Figures 2 and 3 plot the vector of event-study coefficients resulting from the estimation of Equation (1), together with corresponding 95% confidence intervals. In this setting, we are testing whether individuals in teleworkable occupations exhibit a higher propensity to work from home after the pandemic. The outcome is a binary indicator taking value of one in the case of full WFH (Figure 2), or hybrid WFH (Figure 3).

First, we find that both event studies exhibit reasonably parallel trends: All the pre-pandemic 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.

We also detect marked differences in the *persistence* of the effects for the two outcomes. In the case of full WFH, the coefficients drop 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.

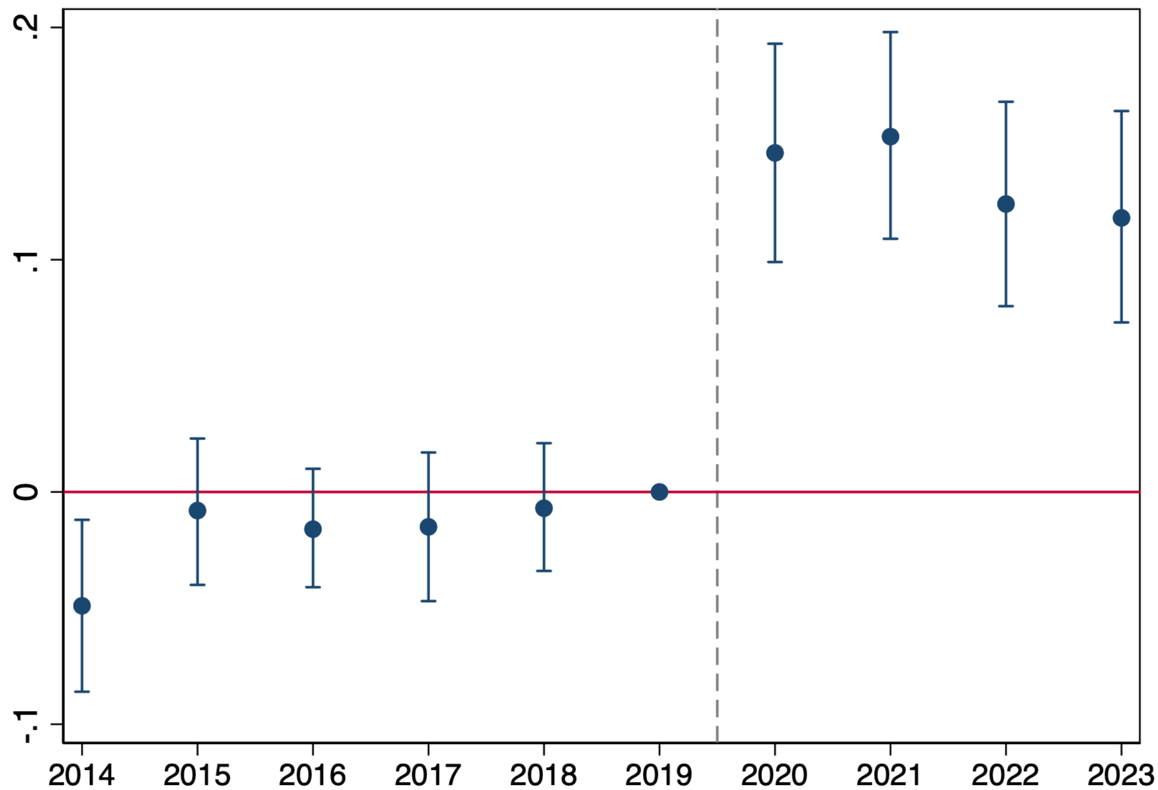
This set of results leads to two conclusions. First, teleworkability is a strong predictor of the evolution of WFH rates after the pandemic, validating the approach that we adopt in the baseline analysis that follows. Second, teleworkability appears to have led to a persistent rise in the availability of partial, rather than full WFH.

Figure 2: Teleworkability and Full 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 variable is a dummy equal to one if the employee works only from home.

Figure 3: Teleworkability and 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 variable is a dummy equal to one if the employee works partially from home.

1.4.2 Teleworkability and Labor Market Outcomes

We now compare workers in teleworkable occupations to their matched controls in nonteleworkable occupations in 2019, leveraging the previous findings of a rise in WFH rates for the former group. Figures 4 through 7 displays event-study coefficients for the key labor market outcomes.

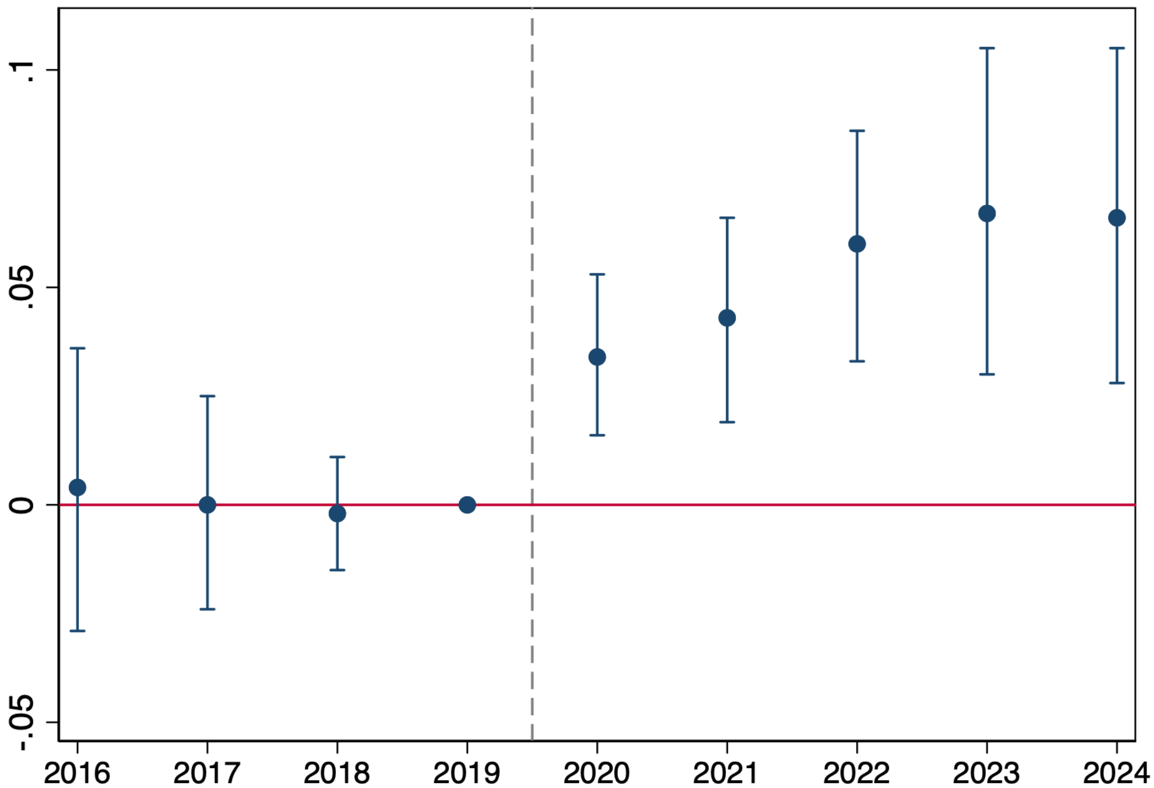
Figure 4 shows no differential pre-trends in log wages for treated and control workers before 2019—which points against possible demand-driven confounding factors. Following the pandemic, workers in teleworkable occupations significantly outperform those in the control group. Indeed, four years after the pandemic, we find that their wages rise by 6.6 logpoints. This effect is significant at the 1% level.

We then decompose this wage premium into two components, namely hours and hourly wage. In Figure 5, 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. The effect on the hourly wage is also significant but smaller, and equal to 0.021 (Figure 6). 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. Figure 7 shows 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).

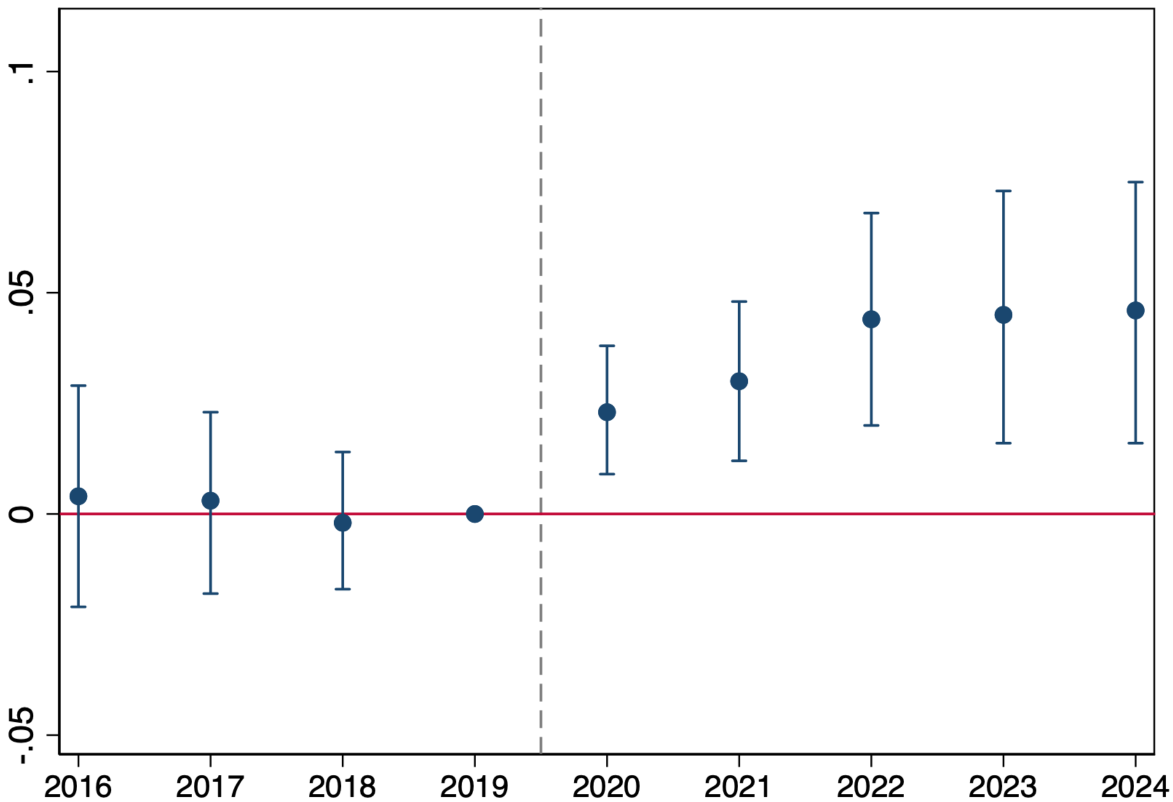
As showed in Appendix Figures 25 through 28, the positive wage effect is present for both men and women, but more pronounced for men. This gap is driven by hourly wages, for which we document a positive effect for men and instead a zero effect for women. The effect on hours is instead quite similar across the two groups.

Figure 4: Teleworkability and Log Wage



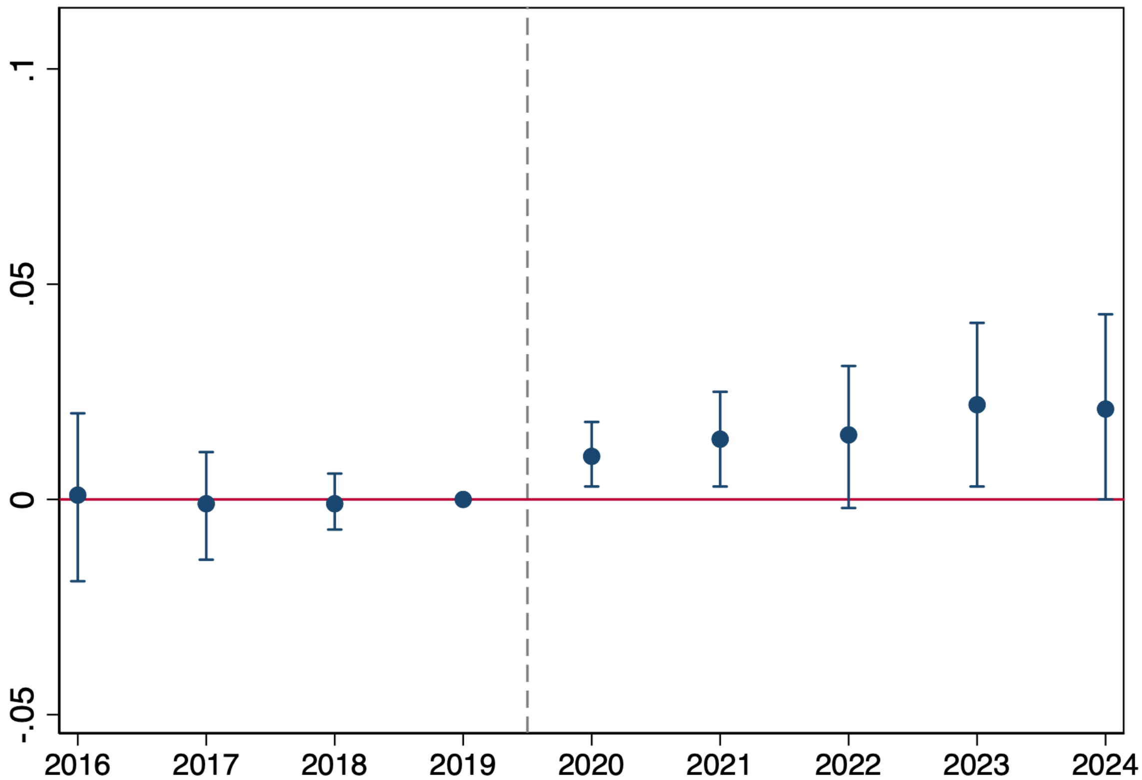
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 logarithm of the worker's wage.

Figure 5: Teleworkability and Log Hours



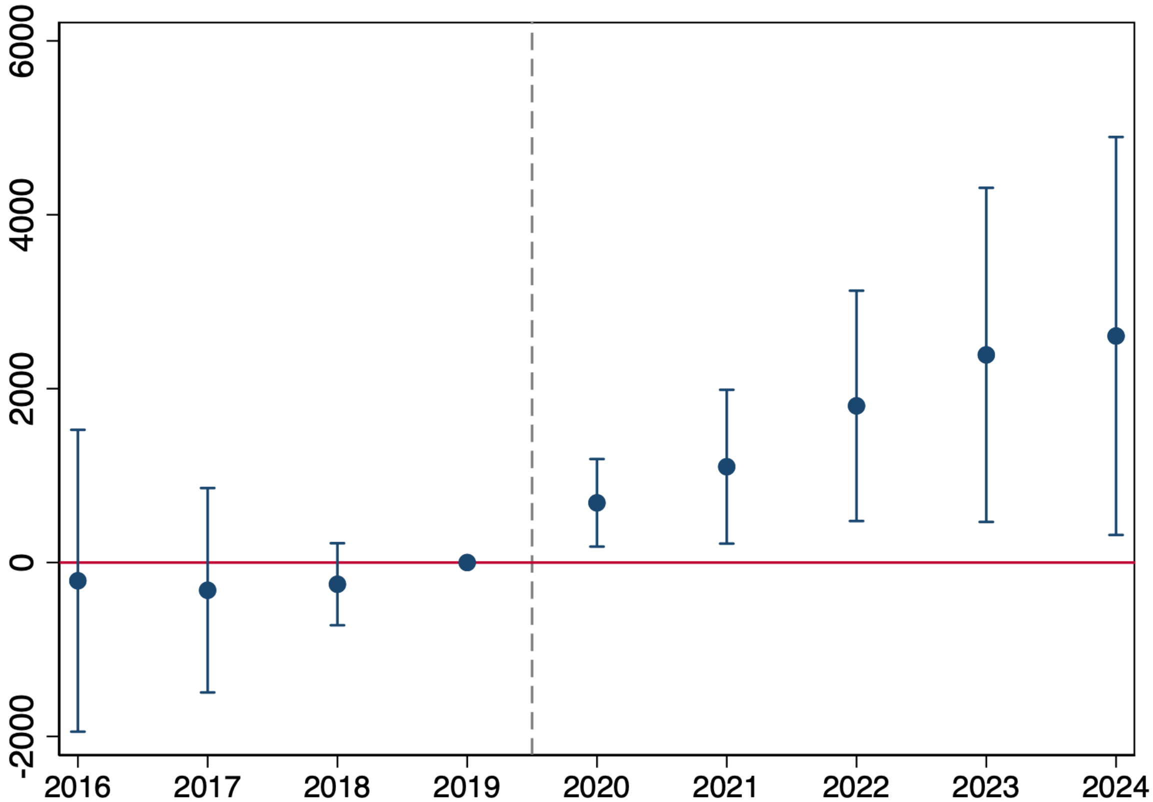
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 logarithm of the worker's hours worked.

Figure 6: Teleworkability and Log Hourly Wage



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 logarithm of the worker's hourly wage.

Figure 7: Teleworkability and Earnings



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 logarithm of the worker's total earnings.

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.

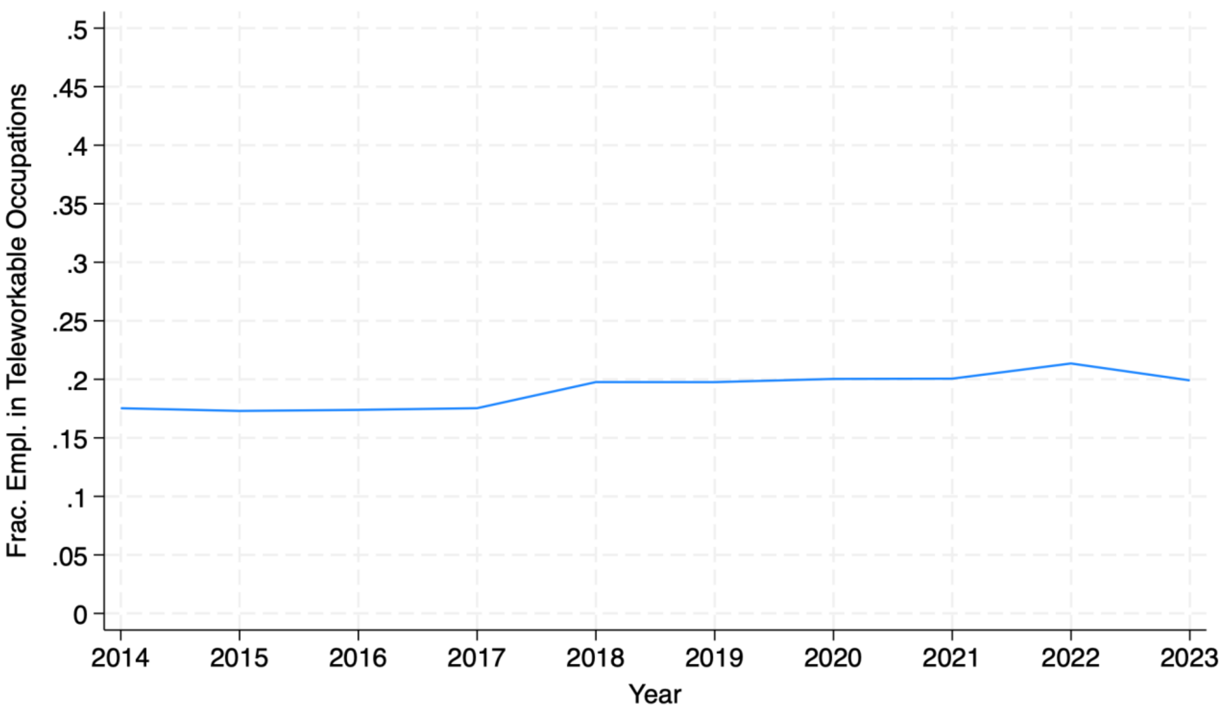
First, recent research has documented that demand-side shifts such automation (Acemoglu and Restrepo, 2022, and Acemoglu and Restrepo, 2019) and the rise of artificial intelligence (Acemoglu et al., 2022, and Acemoglu and Johnson, 2024) have had significant effects on the job market, which might in turn 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 Figure 8, we plot the employment share of workers in teleworkable occupations, using again data from the NEA and EBB surveys.

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 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.

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. (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.) 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.

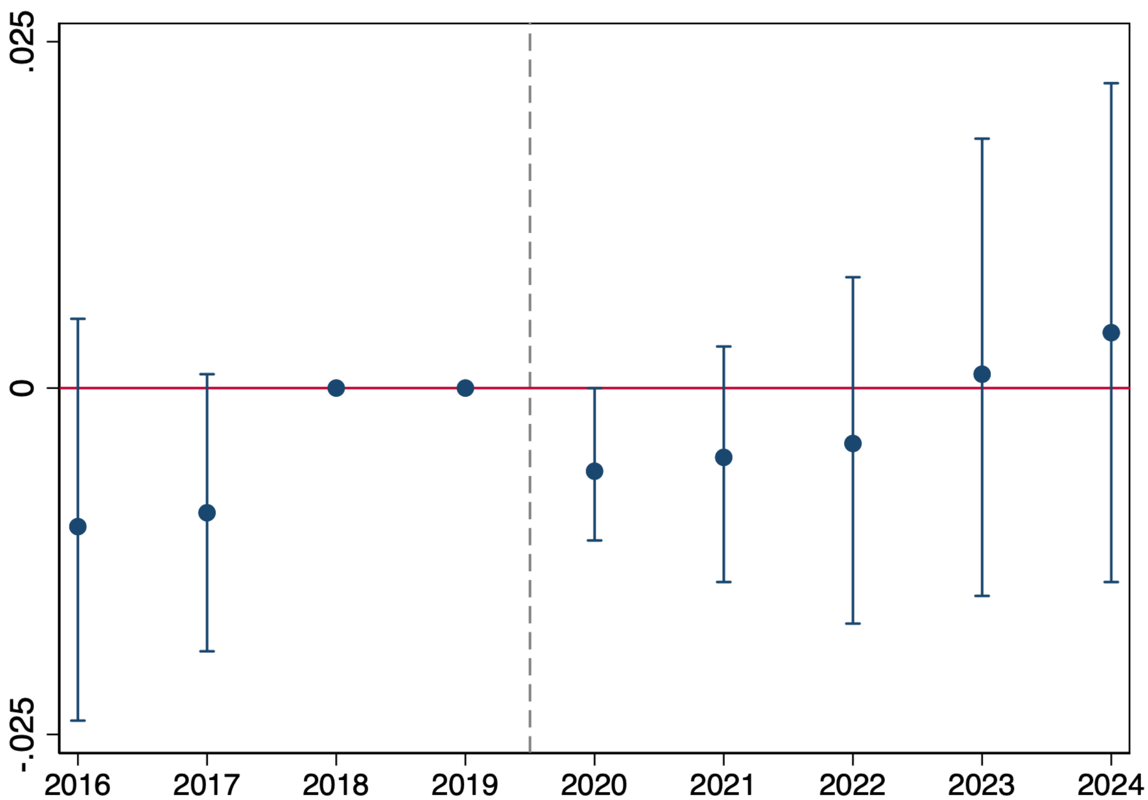
A second concern is that the Covid-19 shock to labor markets was broad, and not limited to the structural increase in the use of WFH arrangements. While this would not be a concern for our approach if this shock affected teleworkable and non-teleworkable occupations in the same way, it is possible that 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 Figure 9, 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). Indeed, the national employment rate went down by just 0.4% in 2020, and already in 2021 bounced above its pre-pandemic levels.

Figure 8: Teleworkability and Employment Shares



Notes: This figure displays the fraction of employees in teleworkable occupations in the EBB and NEA surveys for the years 2014–2023. The teleworkability classification is from Dingel and Neiman (2020).

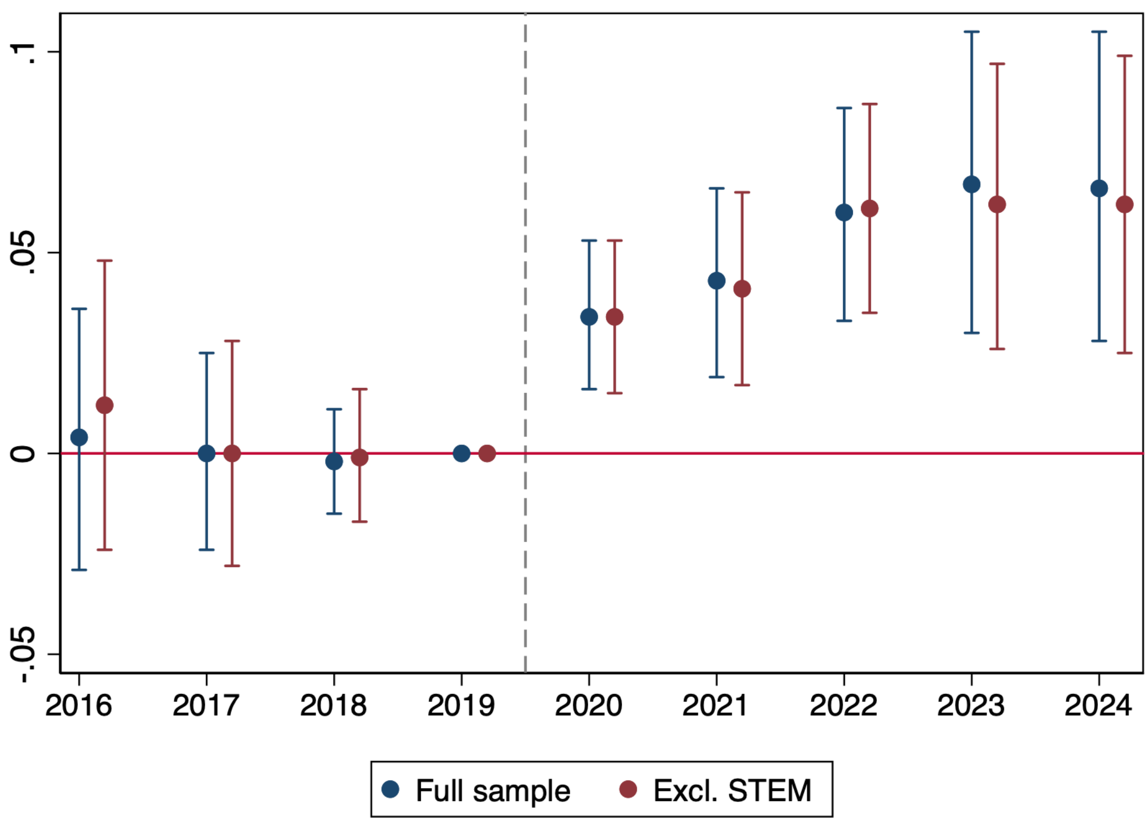
Figure 9: Teleworkability and Employment



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 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.

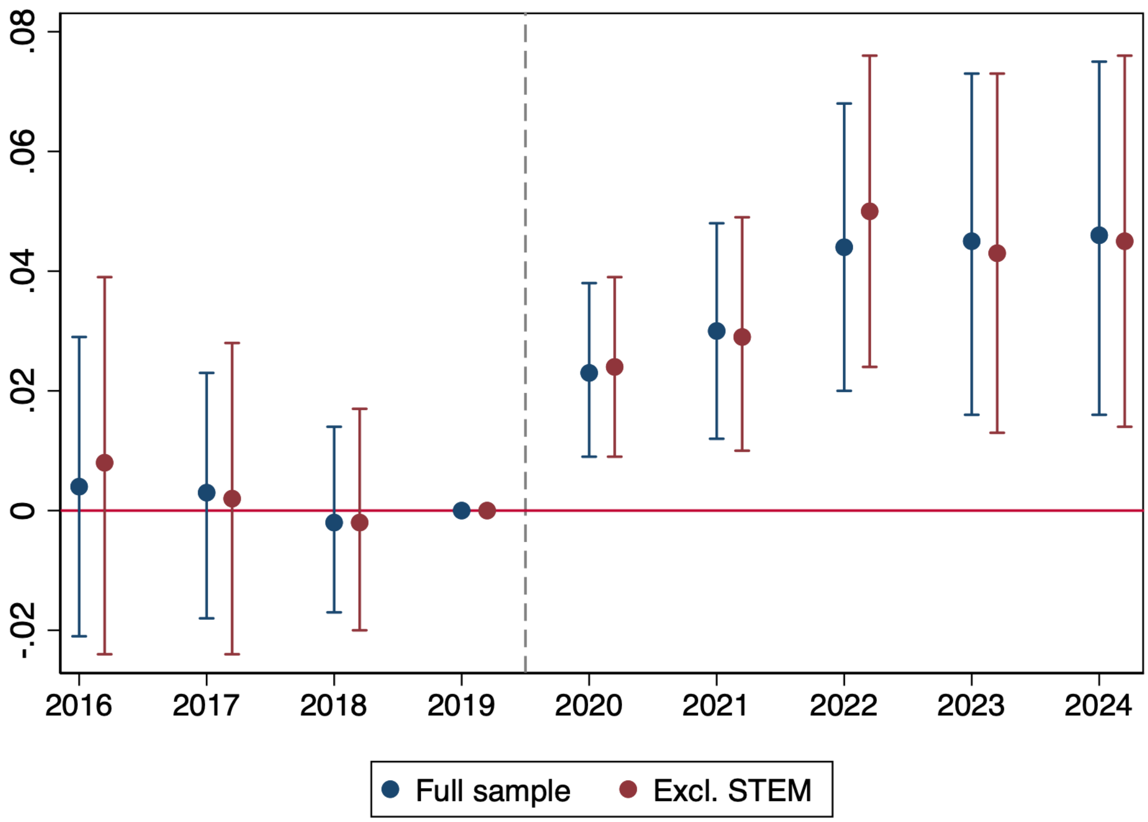
We can also more directly address the confounding factors by excluding the workers who are more likely to be affected by contemporaneous technological shocks. In Figures 10 through 13 we replicate our baseline analysis for both the full sample (in blue) and the subsample of workers for which educational achievement is known and that do not have a STEM degree. 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). For the four key outcomes we examine, excluding workers with a STEM education produces virtually identical results.

Figure 10: Teleworkability and Log Wage – Excluding STEM Workers



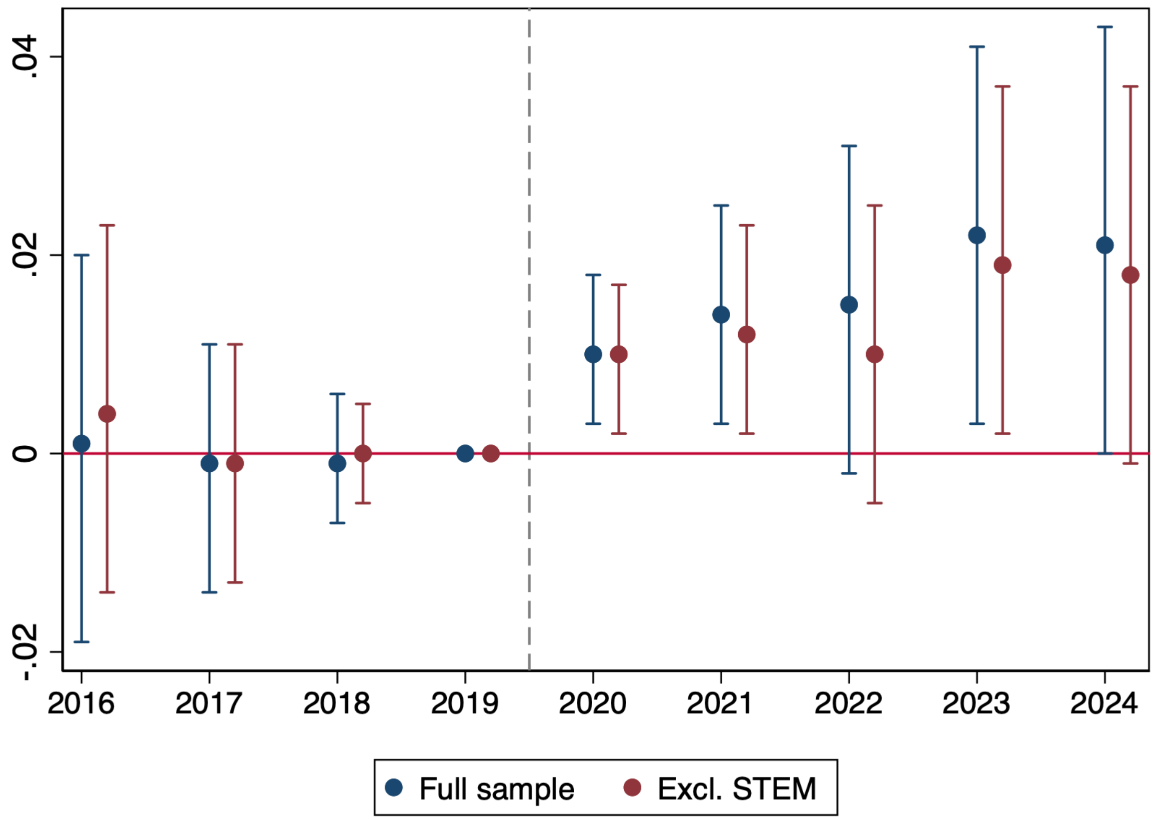
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 variable is the logarithm of the worker's wage.

Figure 11: Teleworkability and Log Hours – Excluding STEM Workers



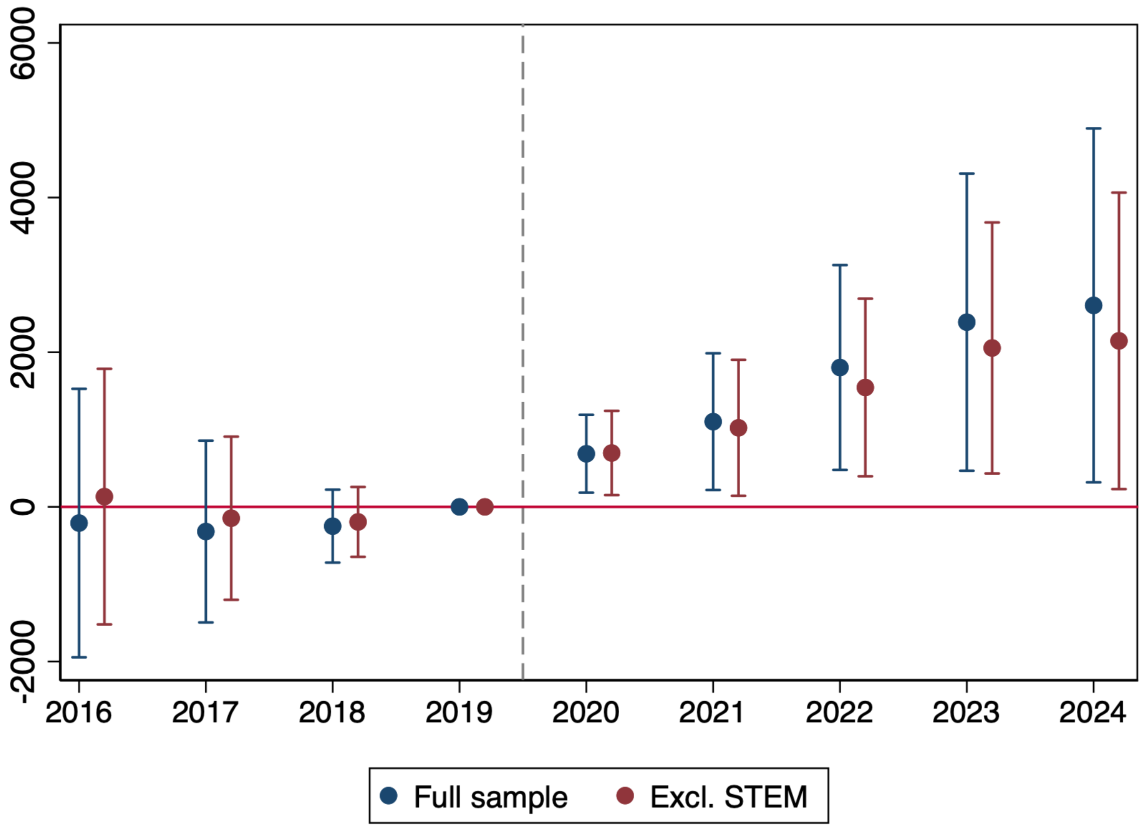
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 variable is the logarithm of the worker's hours worked.

Figure 12: Teleworkability and Log Hourly Wage – 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 variable is the logarithm of the worker's hourly wage.

Figure 13: Teleworkability and Earnings – 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 variable is the logarithm of the worker's total earnings.

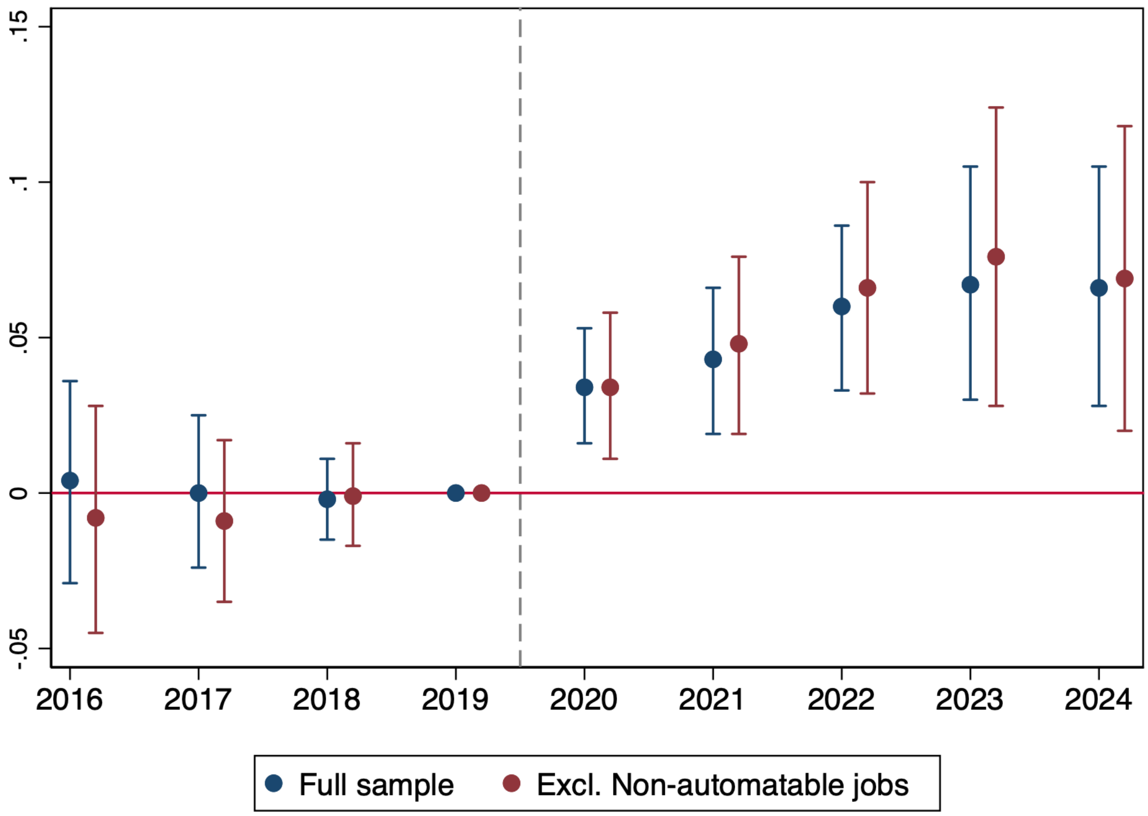
Another key concern that we seek to address is that workers in teleworkable occupations are those least exposed to the risk of automation, which might have differentially affected their earnings. To rule out this possibility, we make use of the "automation exposure" classification developed by the

Labor Market Information (LMI) Institute,[2] 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). 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). 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 Figures 14 to 17 show, 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.

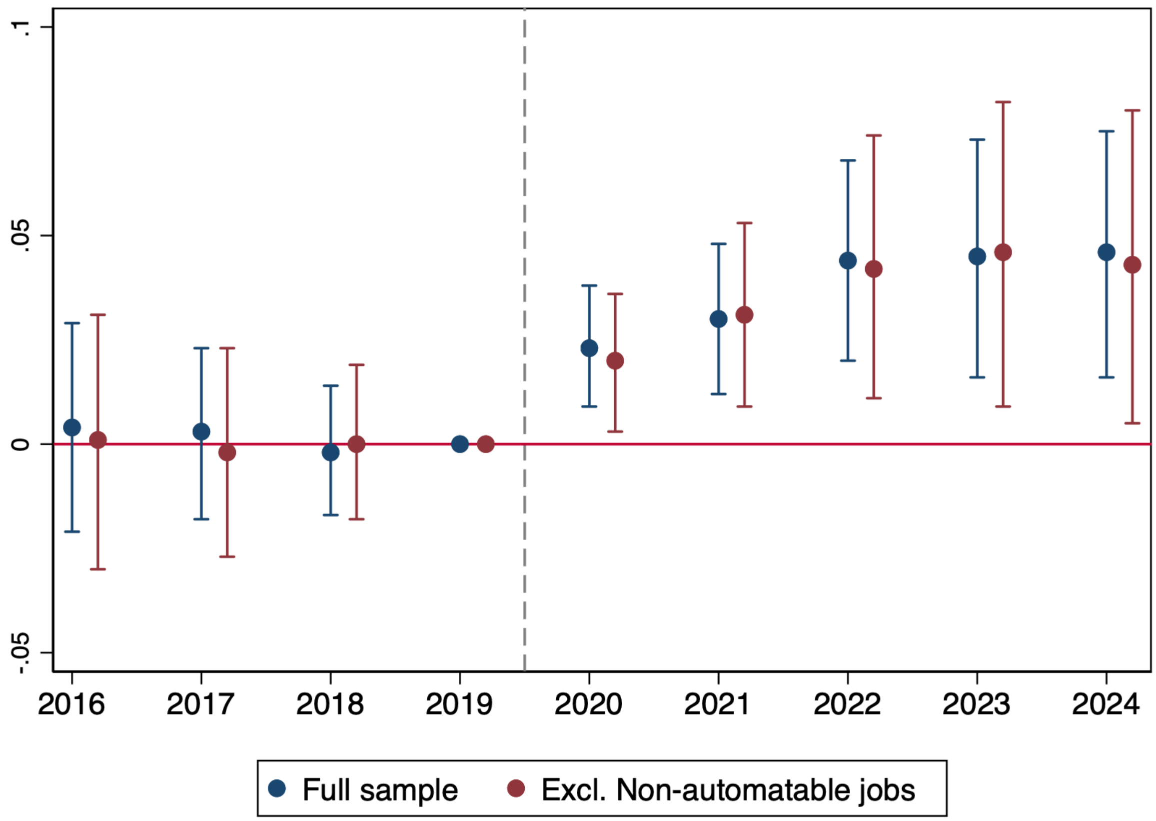
[2] The data can be accessed at https://www.lmiontheweb.org/automation-exposure-score/.

Figure 14: Teleworkability and Log Wage – Excluding Workers With Non-Automatable Jobs



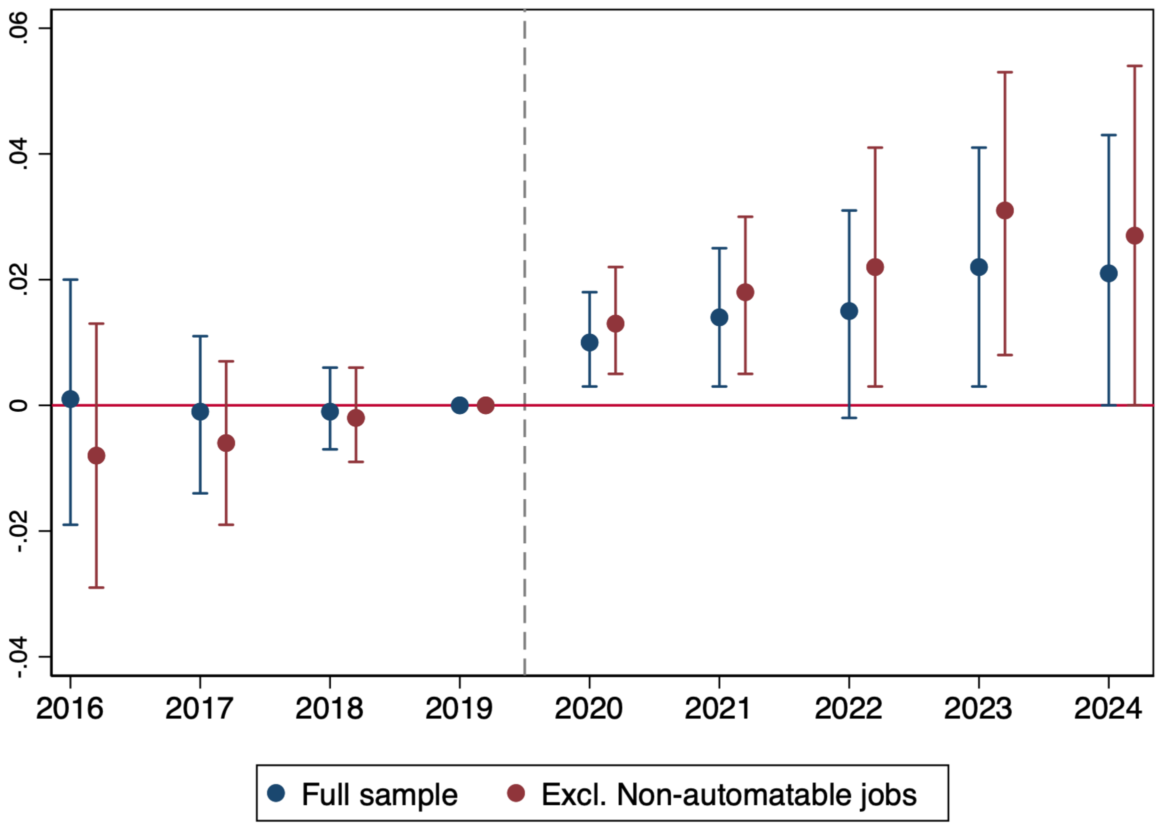
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 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 variable is the logarithm of the worker's wage.

Figure 15: Teleworkability and Log Hours – Excluding Workers With Non-Automatable Jobs



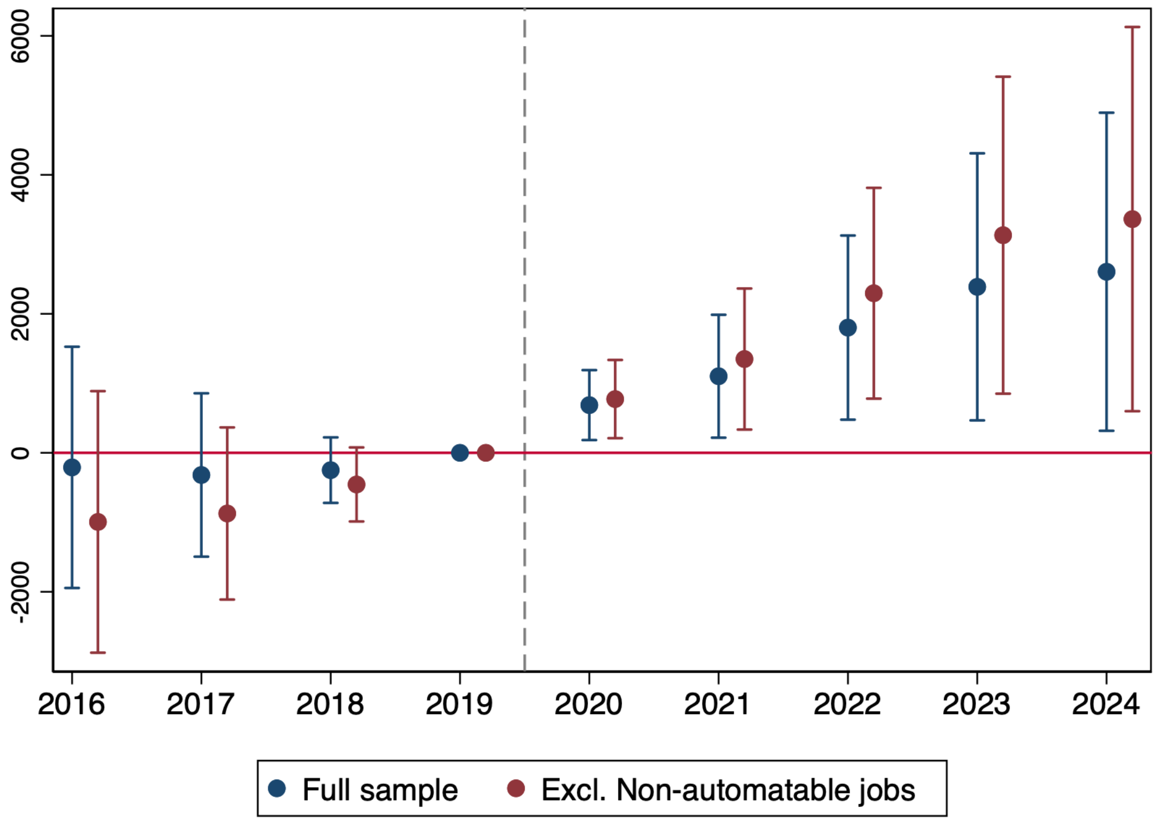
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 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 variable is the logarithm of the worker's hours worked.

Figure 16: Teleworkability and Log Hourly Wage – 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 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 variable is the logarithm of the worker's hourly wage.

Figure 17: Teleworkability and Earnings – Excluding Workers With Non-Automatable Jobs



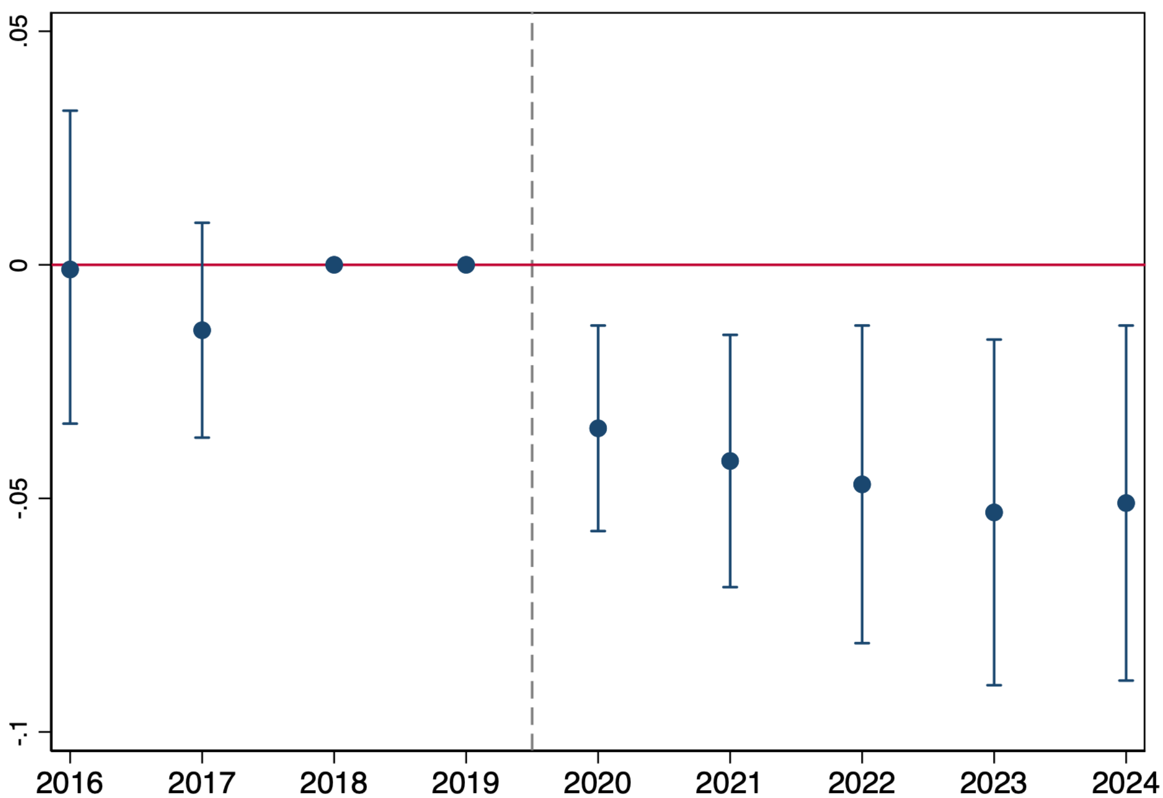
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 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 variable is the logarithm of the worker's total earnings.

1.4.4 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 broadened the potential labor market for jobs that can be performed at home.

We reestimate Equation 2, this time with a dummy equal to one if the employee is employed with their pre-pandemic 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 18, we document *lower* retention rates for treated workers, which are, by 2024, 4.8 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.

Figure 18: Teleworkability and Firm Retention

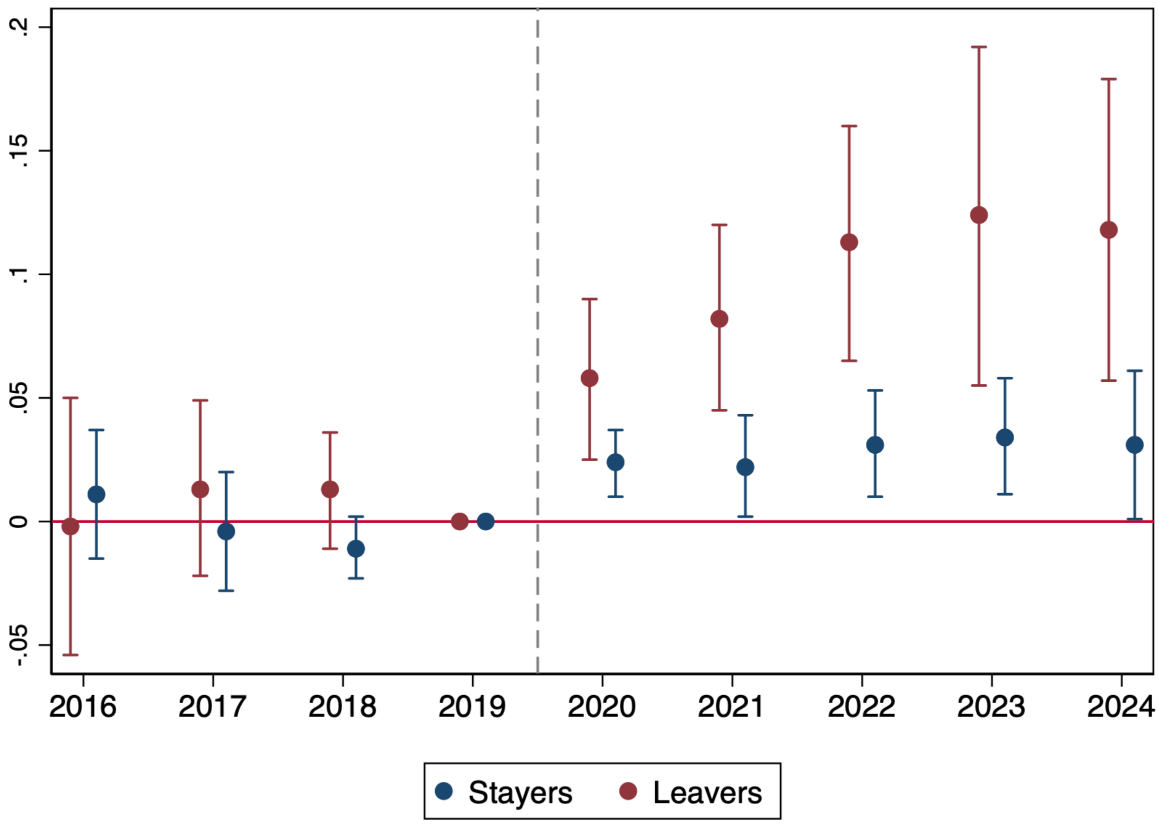


Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic.

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.

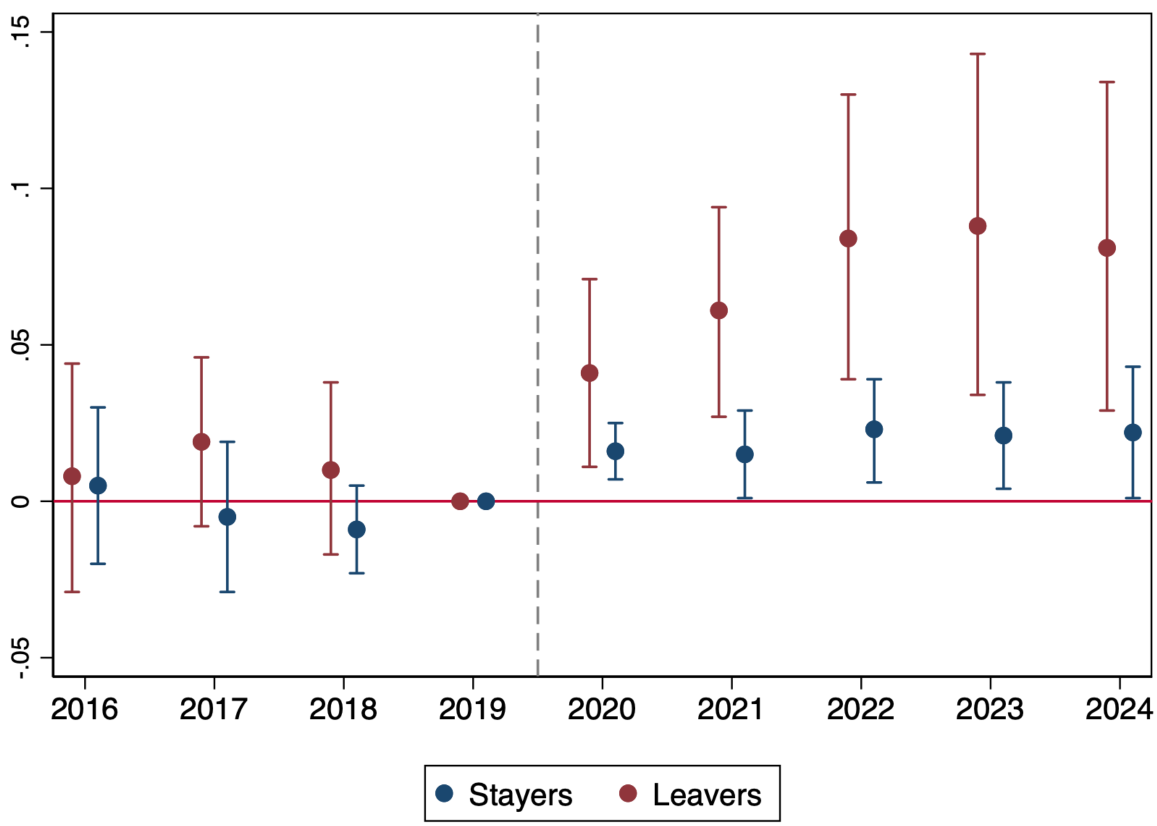
This finding motivates us to examine whether this higher propensity to leave among treated workers can explain their outperformance. We proceed as follows. We define workers as “stayers” if they retain their 2019 employer throughout the years 2020–2024. “Leavers” are instead the workers that are employed at a different firm in any of these five years. 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). Event-study coefficients for these two subsamples are reported in Figures 19 through 22. 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 analogous 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.

Figure 19: Teleworkability and Log Wage – Stayers and Leavers



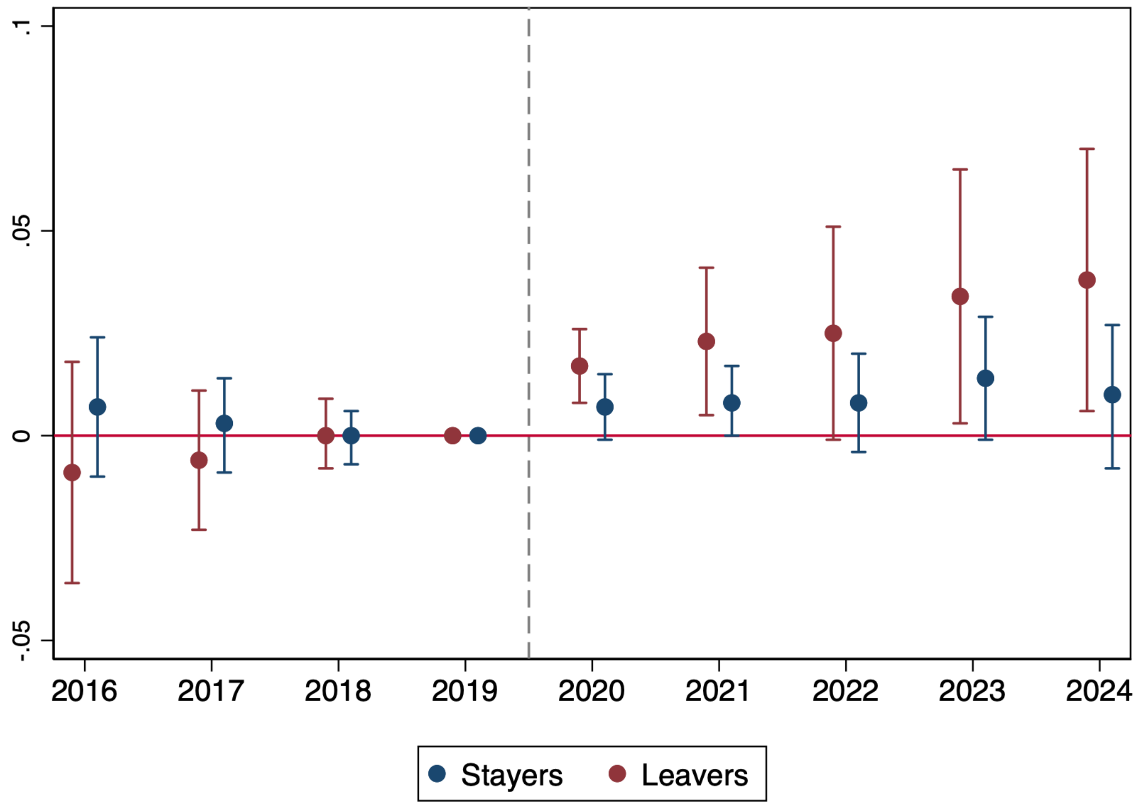
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 variable is the logarithm of the worker's wage.

Figure 20: Teleworkability and Log Hours – Stayers and Leavers



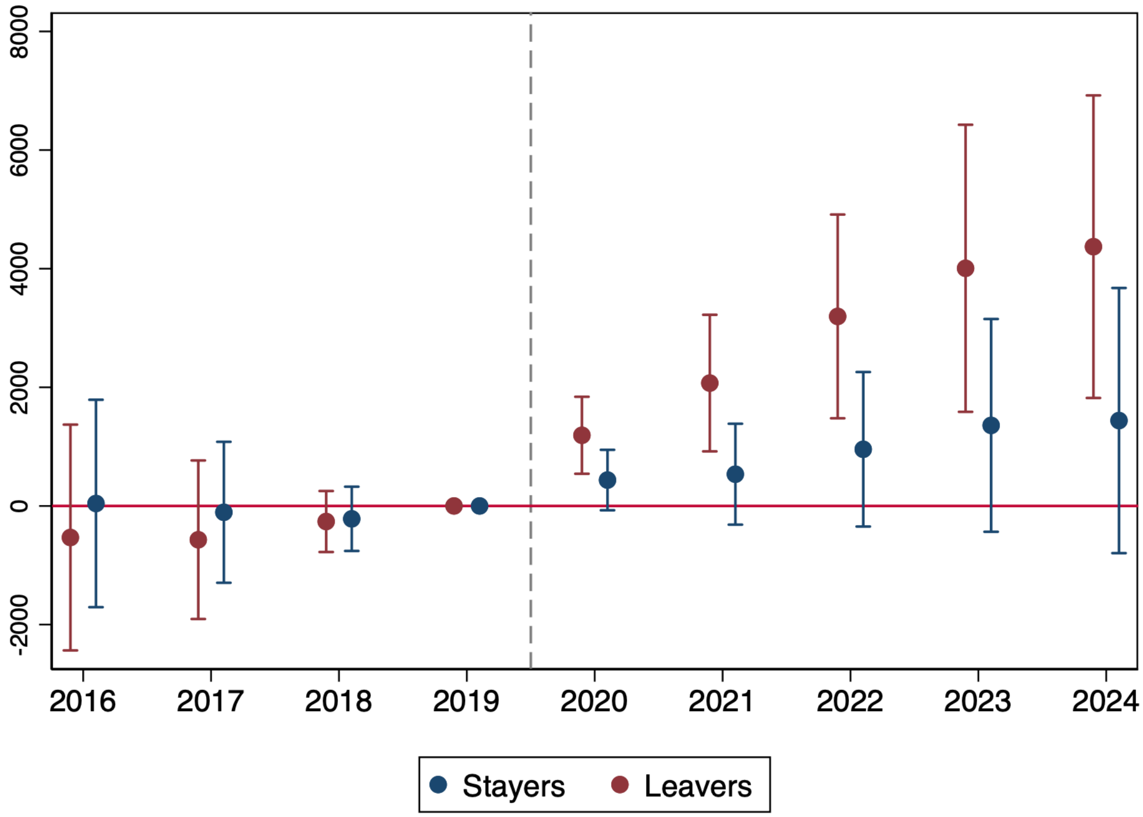
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability 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 variable is the logarithm of the worker's hours worked.

Figure 21: Teleworkability and Log Hourly Wage – 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 variable is the logarithm of the worker's hourly wage.

Figure 22: Teleworkability and Earnings – 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 variable is the logarithm of the worker's total earnings.

1.4.5 Which Workers Move, and Where?

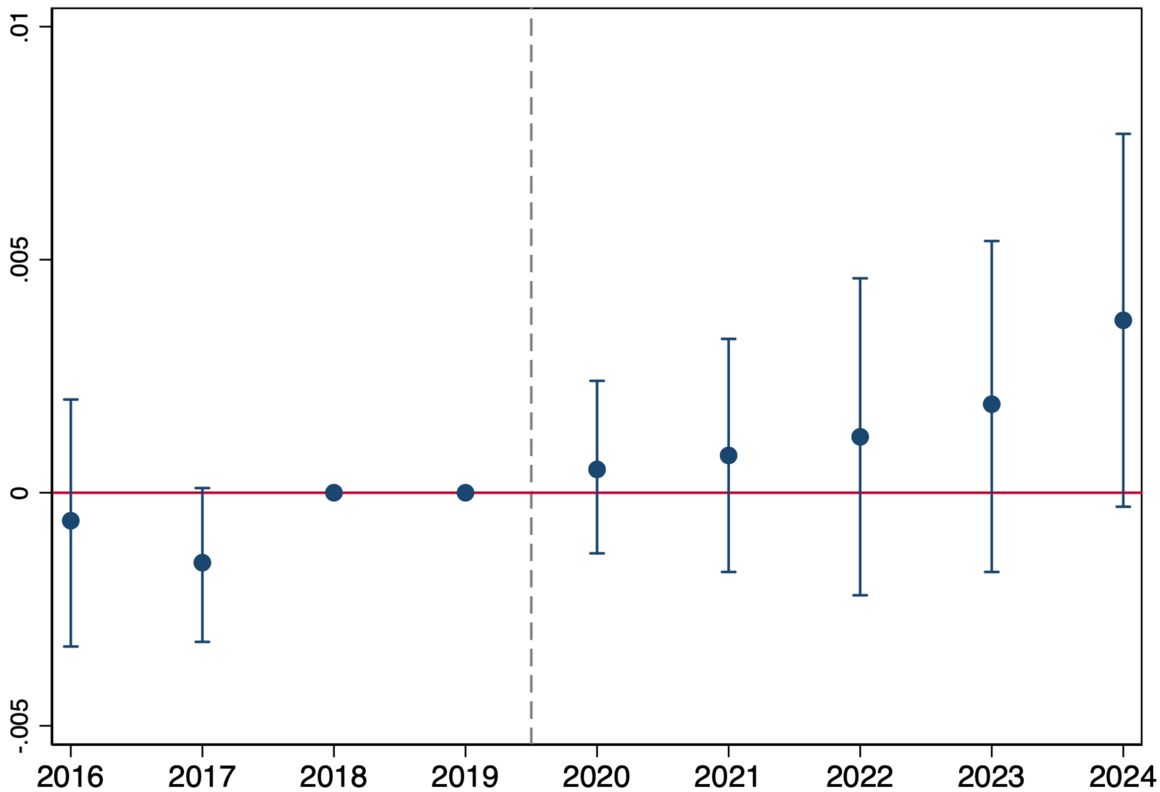
The previous analysis provides some suggestive evidence that, among workers with teleworkable occupations, wage gains are essentially driven by those who leave their original employers. This suggests that WFH availability allows some workers to transition to jobs which grant them the possibility to work more or earn higher hourly wages.

In this section we seek to understand the sources of these gains from job 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).

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 that occurred after the pandemic.

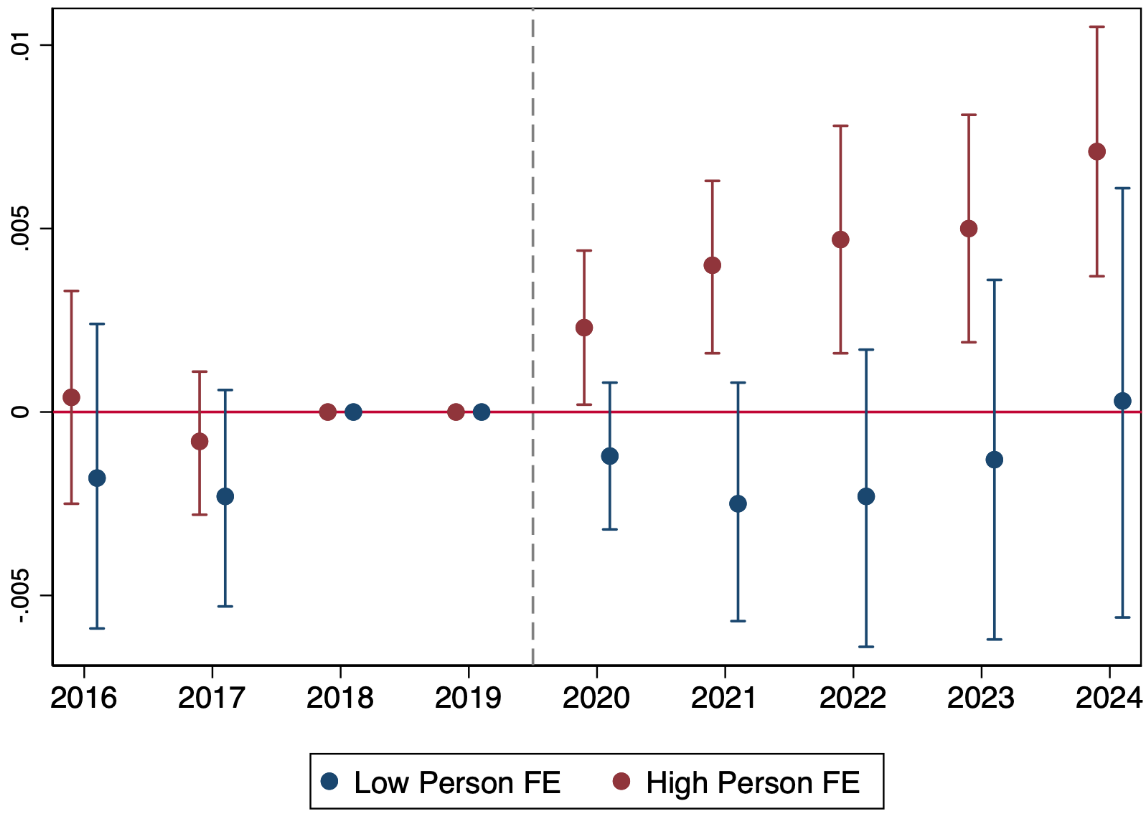
In Figure 23 the dependent variable is the firm wage premium. We detect, as expected, some evidence that workers in teleworkable occupations move towards high-paying firms. However, the estimates do not allow us to draw meaningful conclusions, with all the postevent coefficients being generally insignificant. 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 plot event-study coefficients in Figure 24 for these two subsamples. For high-ability workers (depicted in red), 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.

Figure 23: Teleworkability and Firm Wage Premia – Full Sample



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.

Figure 24: Teleworkability and Firm Wage Premia – 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. Here, 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.

1.5 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, nor to a lower vulnerability of their jobs to automation. Moreover, 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.

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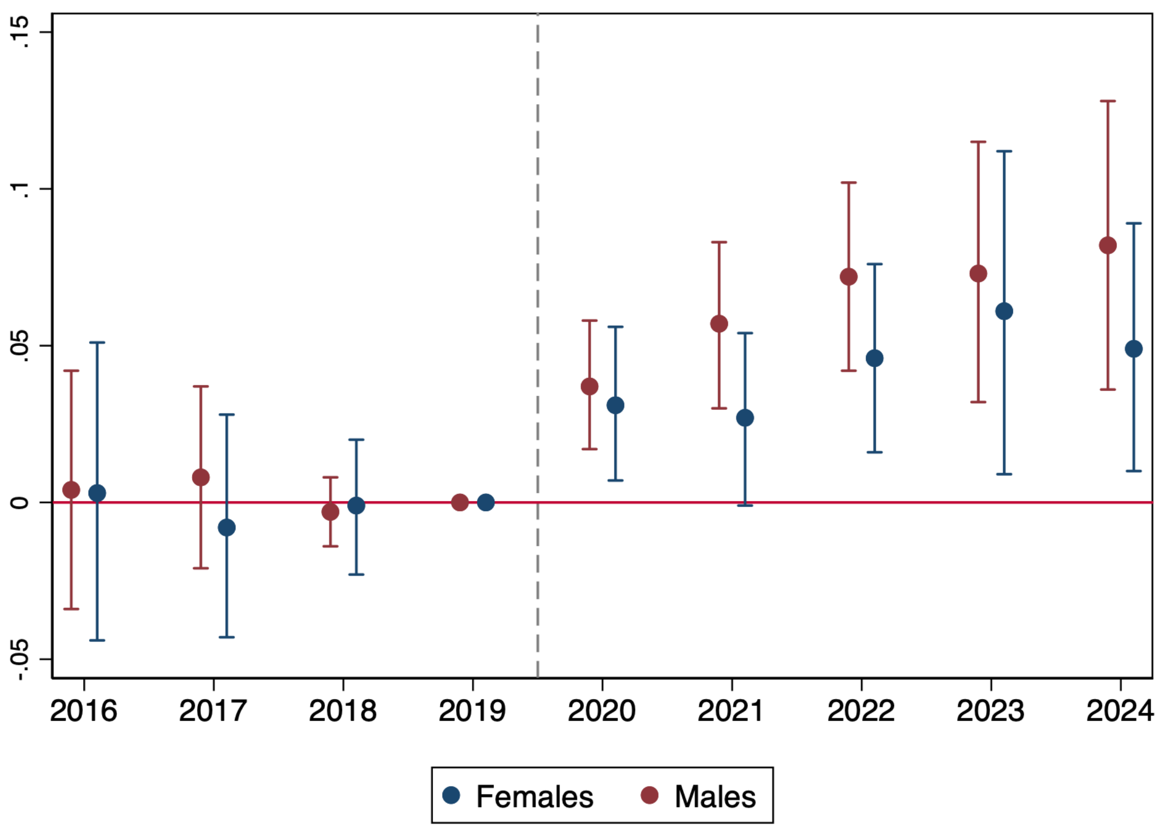
Appendix

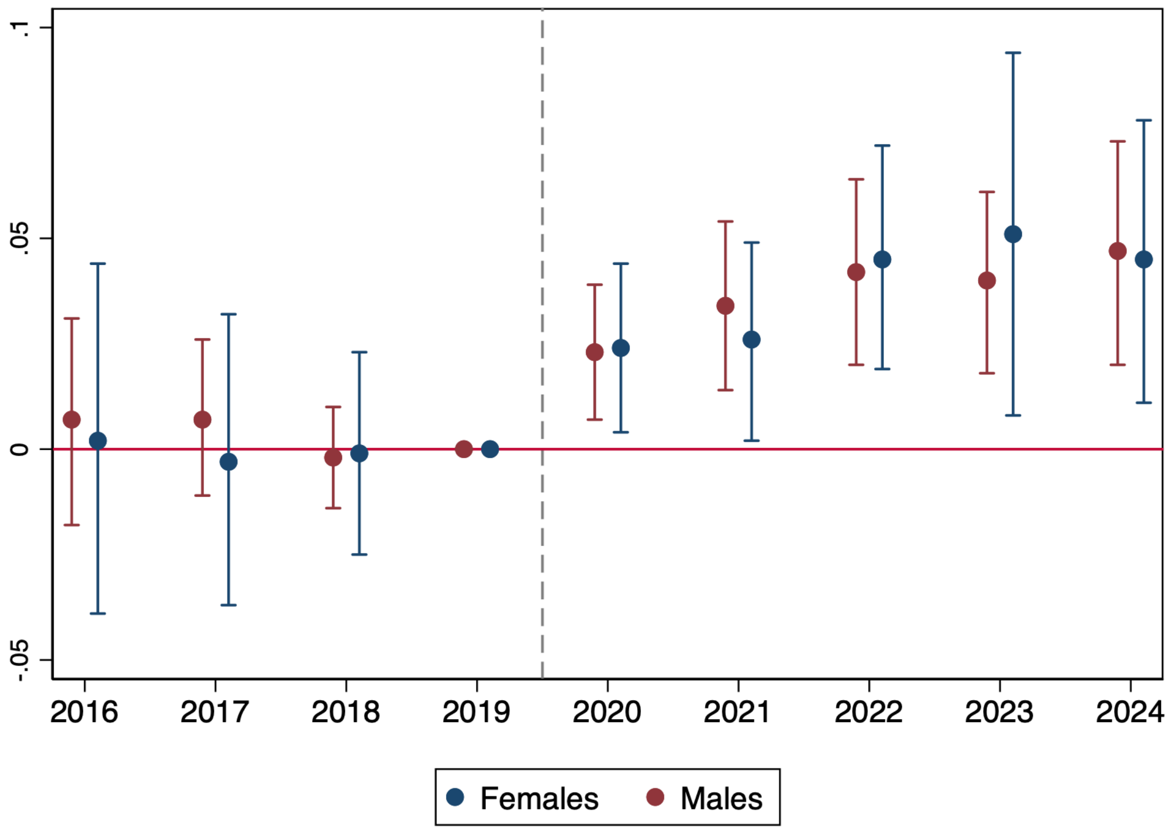
This appendix reports different figures omitted from the main text for brevity. Figure 25 through 28 report coefficients from event-study where we distinguish between men and women.

Figure 25: Teleworkability and Log Wage – Heterogeneity by Gender



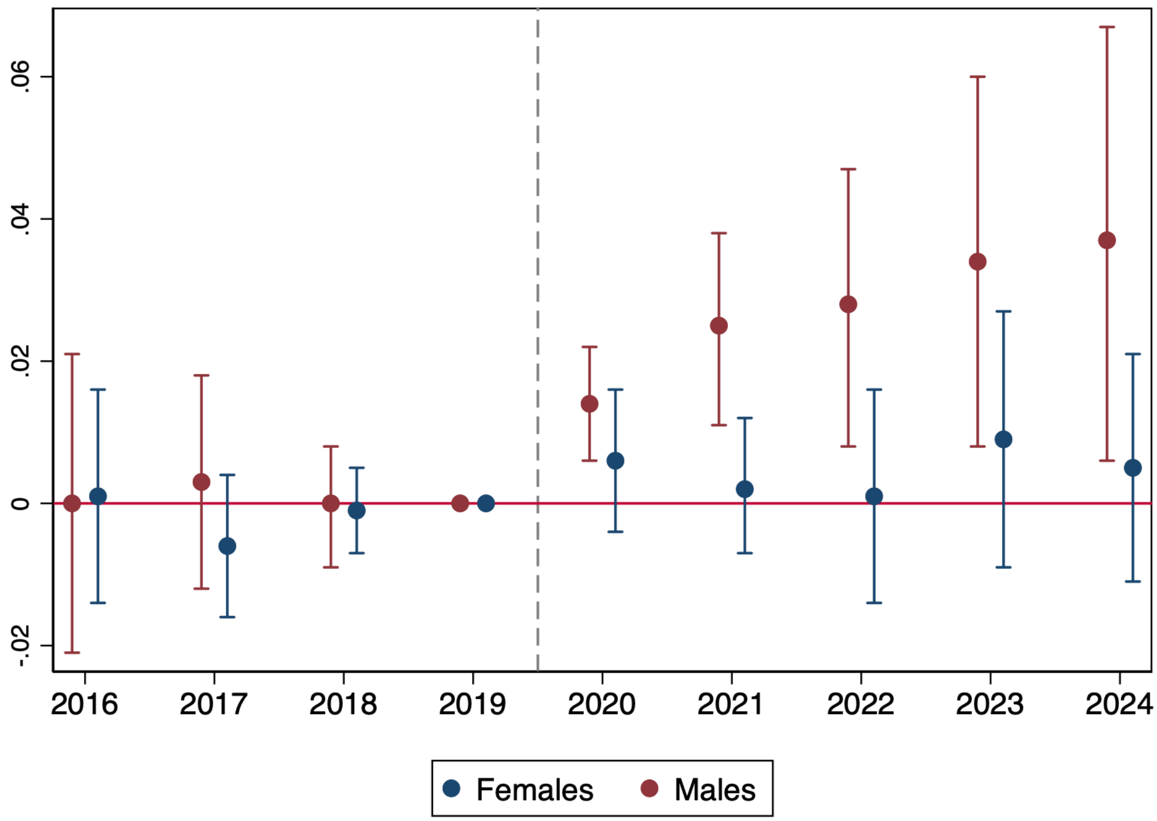
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability classification is from Dingel and Neiman (2020) and the sample is obtained after performing the matching procedure described in Section 3.2. We plot separately coefficients for women (in blue) and men (in red). We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variable is the logarithm of the worker's wage.

Figure 26: Teleworkability and Log Hours – Heterogeneity by Gender



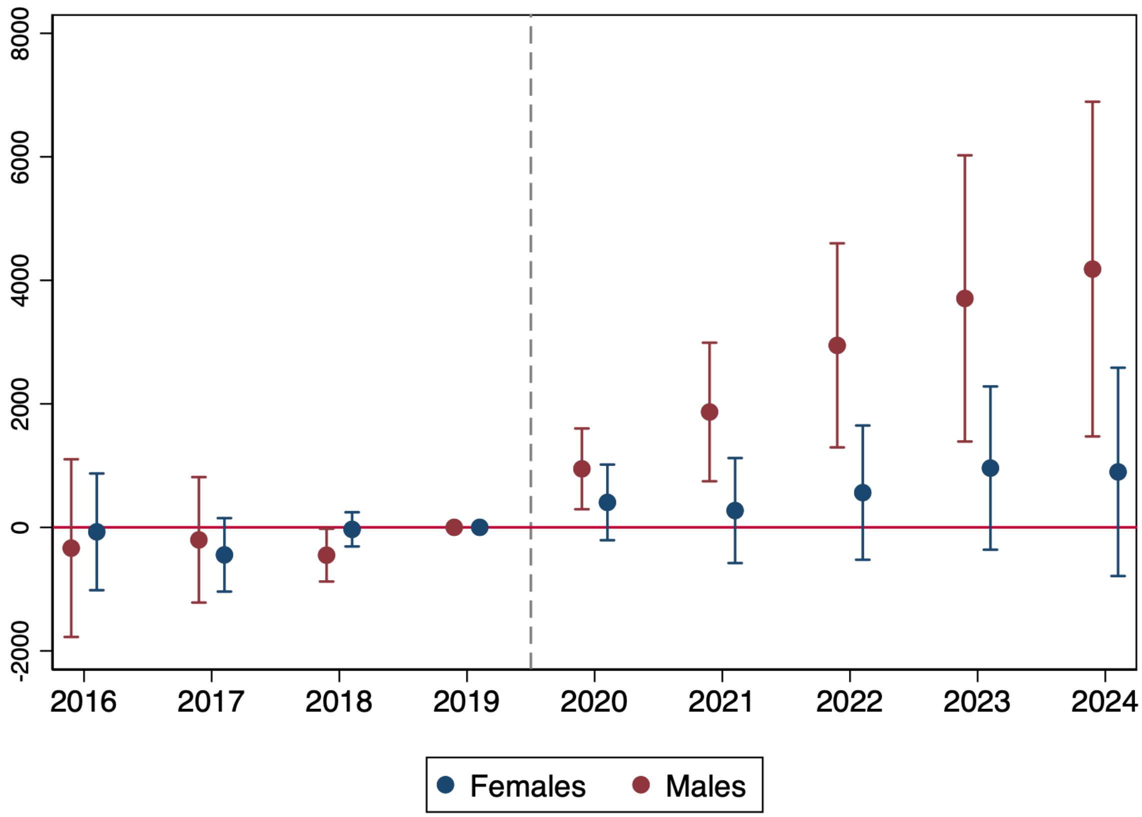
Notes: This figure displays event-study coefficients with corresponding 95% confidence intervals obtained after estimating Equation (2), where we compare labor market outcomes of workers in teleworkable and non-teleworkable occupations in the years surrounding the COVID-19 pandemic. The teleworkability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

Figure 27: Teleworkability and Log Hourly Wage – Heterogeneity by Gender



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 separately coefficients for women (in blue) and men (in red). We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variable is the logarithm of the worker's hourly wage.

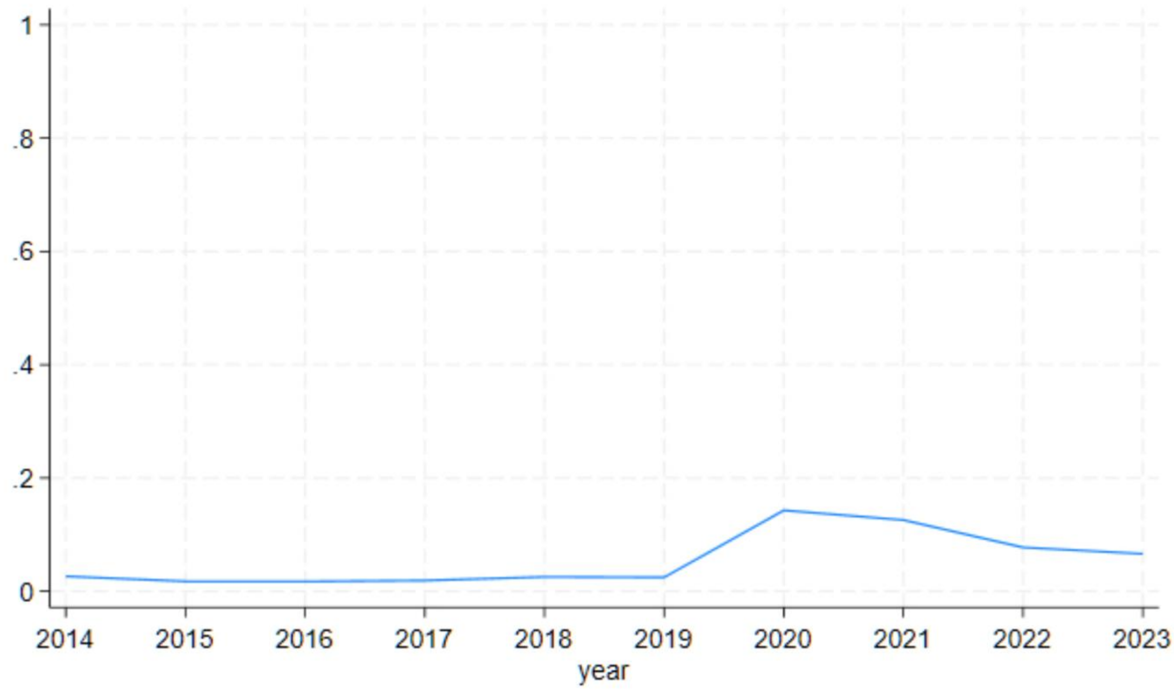
Figure 28: Teleworkability and Earnings – Heterogeneity by Gender



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 separately coefficients for women (in blue) and men (in red). We control for worker fixed effects and year fixed effects, and standard errors are clustered at the occupation level. The dependent variable is the logarithm of the worker's total earnings.

Figure 29 reports the fraction of workers who engage in full teleworking across the NEA surveys 2014-2023. There is a clear spike in 2020, followed by a partial reversal

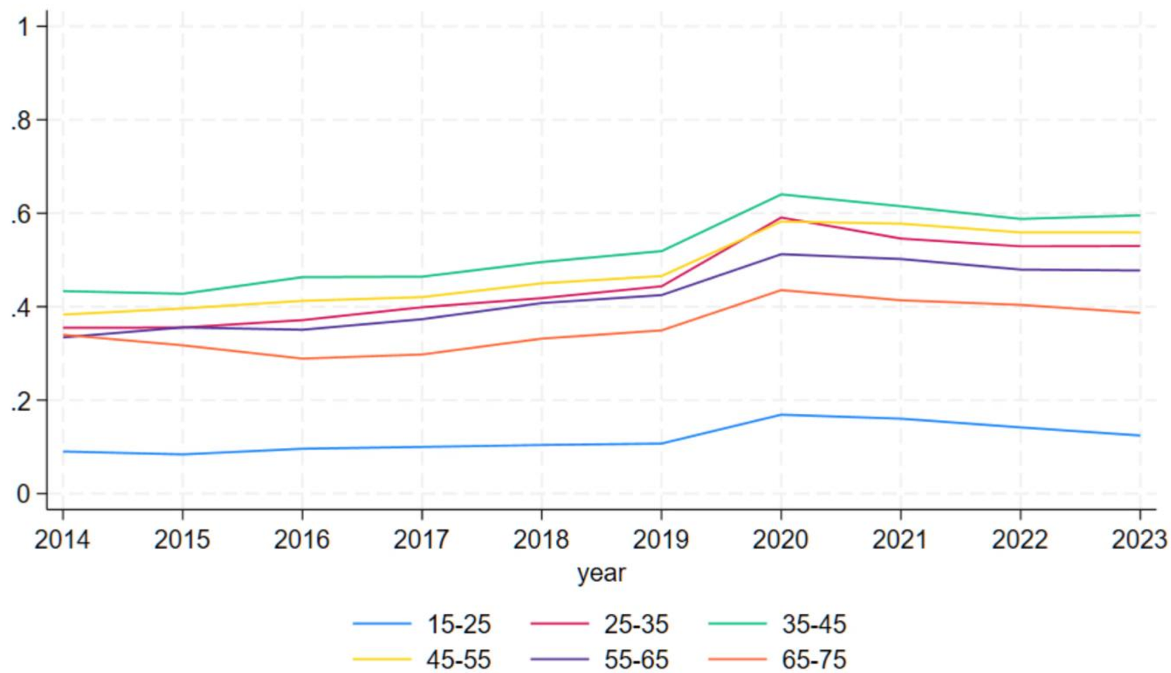
Figure 29: Trends in Full Work-from-Home



Notes: This figure displays the fraction of workers in the NEA surveys 2014-2023 who claim to fully work from home for different age groups.

Figure 30 reports the fraction of workers who engage in partial or full teleworking for different age groups. If we exclude the youngest age bin (which include very few workers) there is a clear negative relationship between age and work-from-home. This suggests that it might be harder for older workers to adapt to the use of technologies needed for teleworking.

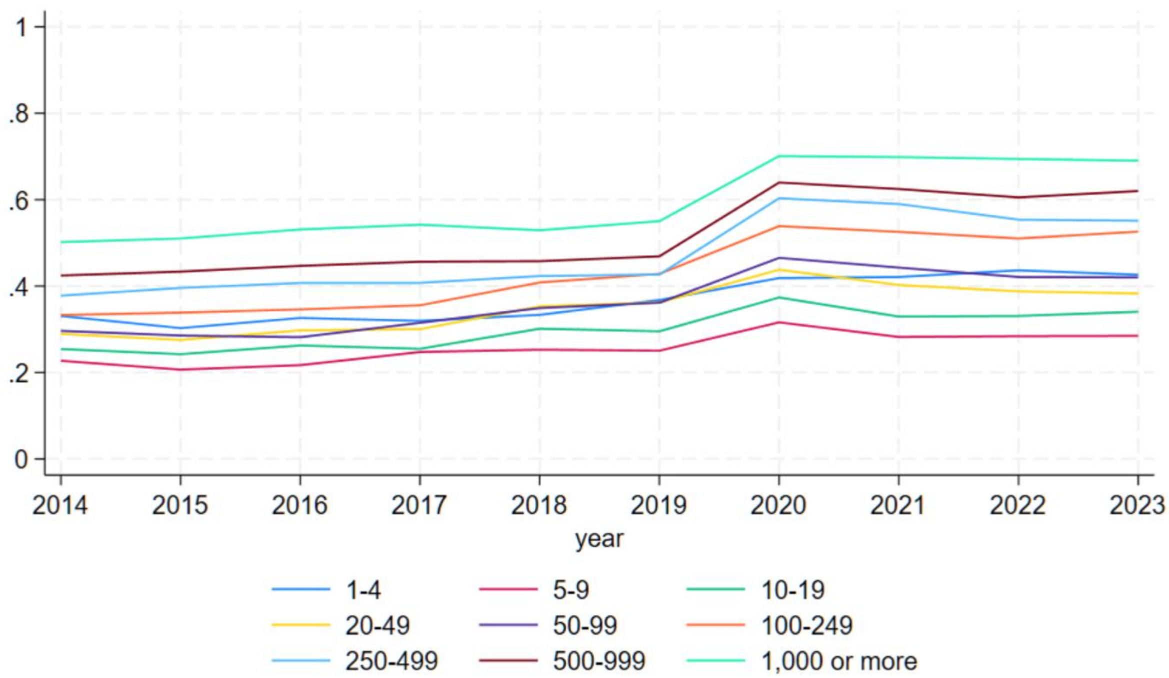
Figure 30: Teleworking and Age



Notes: This figure displays the fraction of workers in the NEA surveys 2014-2023 who claim to work fully or partially from home for different age groups.

Figure 31 reports the fraction of workers who engage in partial or full teleworking for different firm size groups. There is an apparent monotonic relation between firm size and work-from-home, which suggests that large firms have more flexible and adaptive organizational structures.

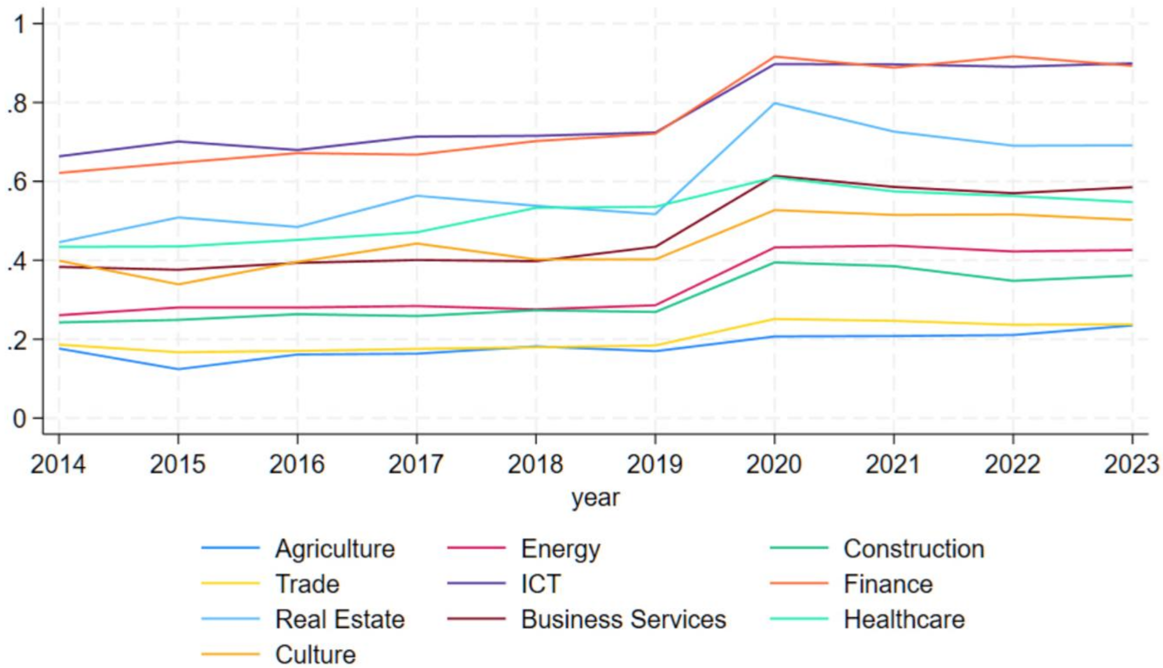
Figure 31: Teleworking and Firm Size



Notes: This figure displays the fraction of workers in the NEA surveys 2014-2023 who claim to work fully or partially from home for different employer sizes.

Figure 32 reports the fraction of workers who engage in partial or full teleworking for different industries. With the exception of trade and agriculture, all experience a pronounced spike after the pandemic.

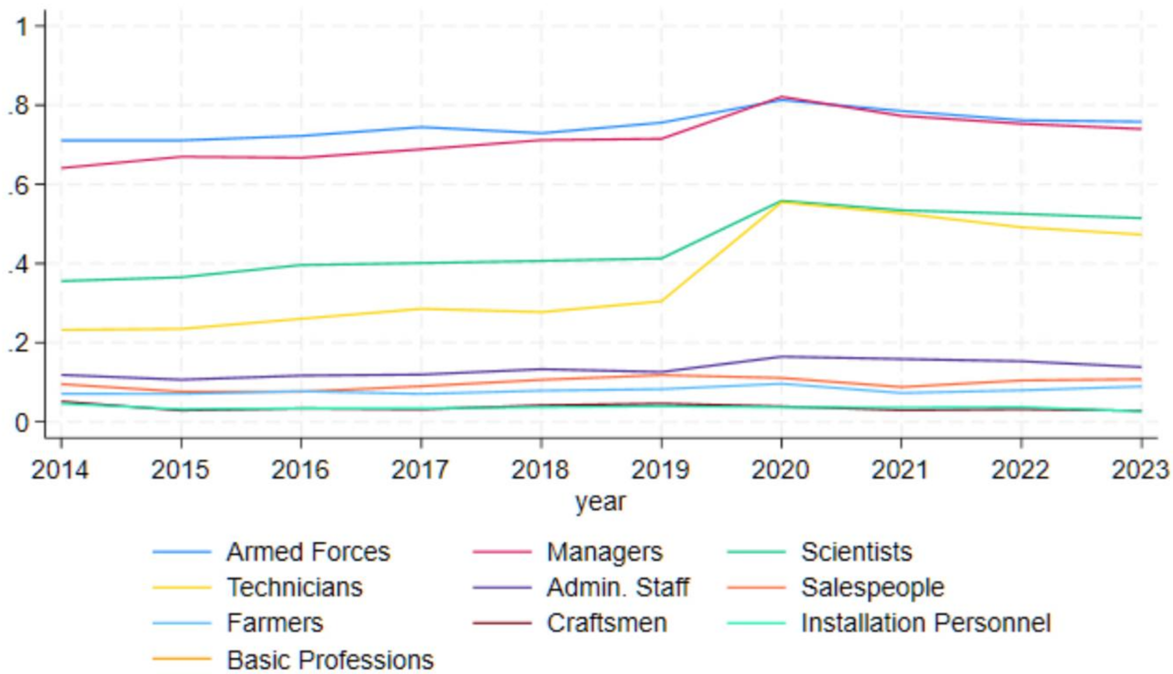
Figure 32: Teleworking and Industries



Notes: This figure displays the fraction of workers in the NEA surveys 2014-2023 who claim to work fully or partially from home in different industries.

Figure 33 reports the fraction of workers who engage in partial or full teleworking for different occupations. Teleworking is concentrated in four occupations: armed forces, managers, scientists, and technicians. The other occupations are largely unresponsive to the pandemic shock.

Figure 33: Teleworkability and Occupations



Notes: This figure displays the fraction of workers in the NEA surveys 2014-2023 who claim to work fully or partially from home in different occupations.

2. Survey Evidence on Work-from-Home and Occupations

2.1. Introduction

Work-from-home has become a prominent feature of the labor market in the European economy. This chapter presents descriptive evidence regarding its presence, following the COVID-19 pandemic, with a special emphasis on the five largest European economies and on the heterogeneity with regard to the occupation.

We first present survey evidence from the European Skills and Jobs Survey (ESJS) **(**Cedefop, 2021)**,** showing that the fraction of individuals who claim to work more often away from their employer has grown substantially. Importantly, this effect is heterogeneous and greatly depends on the occupation of the worker. Specifically, we show that, when using Dingel and Neiman (2020)'s *teleworkability* classification, the growth is concentrated in "teleworkable" occupations. This descriptive evidence is then further supported by a formal econometric analysis.

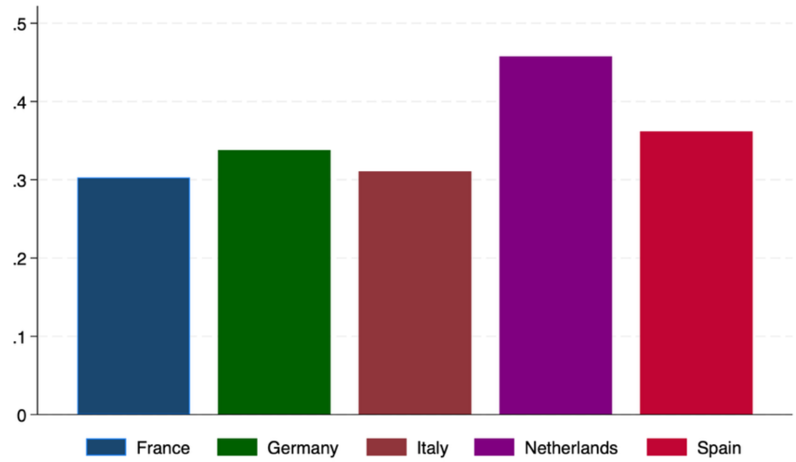
2.2. Work-from-Home After the Pandemic

This section presents descriptive evidence from the ESJS. We focus on the Wave 2 survey (Pouliakas and Souto Otero, 2022), which is the first survey reporting postpandemic evidence. The survey collects information on skill requirements, mismatch, learning, and well-being of workers from the 27 EU member states (see Redmond, Brosnan, and Kelly, 2024, for more details).

We focus in particular on the answer to the question "Compared with the situation before the Covid-19 pandemic, do you now experience any of the following situations in your main job? You work more time away from your employer's premises (e.g. remotely from home)." While this question does not map exactly to the question asked in the Dutch NEA survey, a high frequency of "yes" answers suggests that employees can presumably work more often from home than prior to the pandemic.

In Figure 34, we show that the frequency of participants who respond "yes" to the question is fairly high, ranging between 30% (France) and 46% (the Netherlands). The fraction of workers responding yes in the full sample is 34%, suggesting that these five economies are fairly representative of the labor markets in the EU.

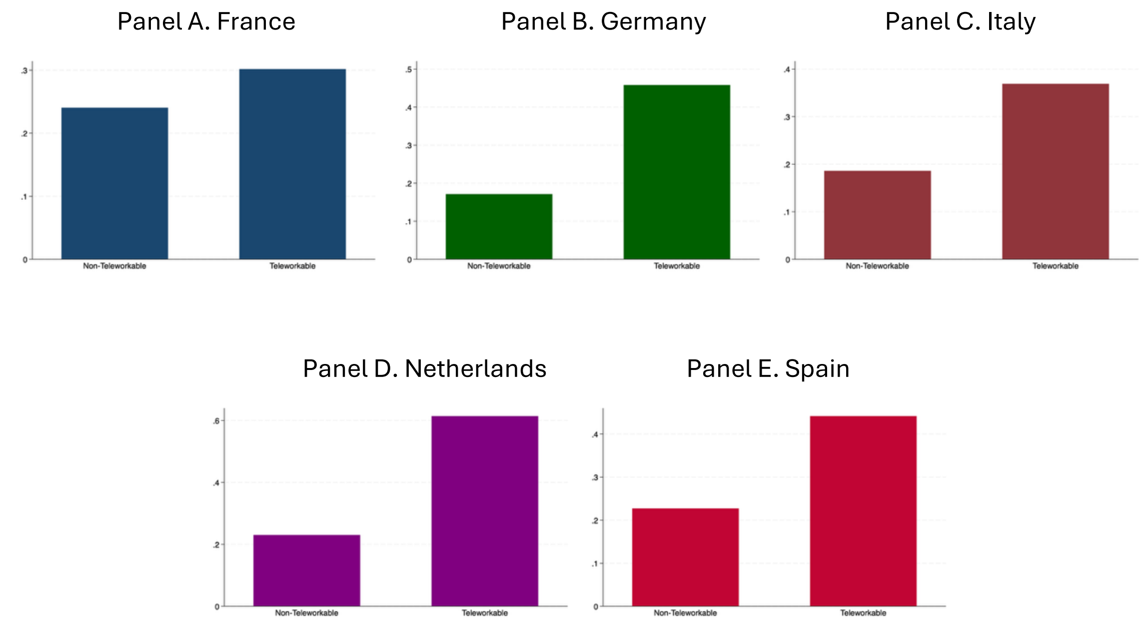
Figure 34: Work-from-Home in the 5 Largest European Economies



Notes: This table reports the fraction of survey participants who respond “yes” to the question “Compared with the situation before the Covid-19 pandemic, do you now experience any of the following situations in your main job? You work more time away from your employer’s premises (e.g. remotely from home)” for the five largest EU economies.

In Figure 35 we split the sample according to whether workers are employed in teleworkable or non-teleworkable occupations, as reported in Tables 5 and 6 in the Appendix. The teleworkability classification is from Dingel and Neiman (2020) and is described in greater detail in the first chapter of this deliverable. We find that the increase in teleworking is highly concentrated in teleworkable occupations. Except for France, where there is not much of a gap between the workers in teleworkable and non-teleworkable occupations, we find a large difference in the fraction of participants who claim to work away from the employer’s facilities, depending on their occupation. In the other four countries, the gap ranges between 18% gap in Italy and 39% in Germany.

Figure 35: Work-from-Home in the 5 Largest European Economies: Teleworkable and Non-Teleworkable Occupations



Notes: This table reports the fraction of survey participants who respond "yes" to the question "Compared with the situation before the Covid-19 pandemic, do you now experience any of the following situations in your main job? You work more time away from your employer's premises (e.g. remotely from home)" for the five largest EU economies, separately for workers in teleworkable and non -teleworkable occupations.

The next section presents formal evidence that this gap is a robust feature of the data even after controlling for observable worker's characteristics.

2.3. Econometric Evidence

To test whether the association between teleworkability and propensity to work from home persists after controlling for workers' characteristics, we estimate the following linear probability model:

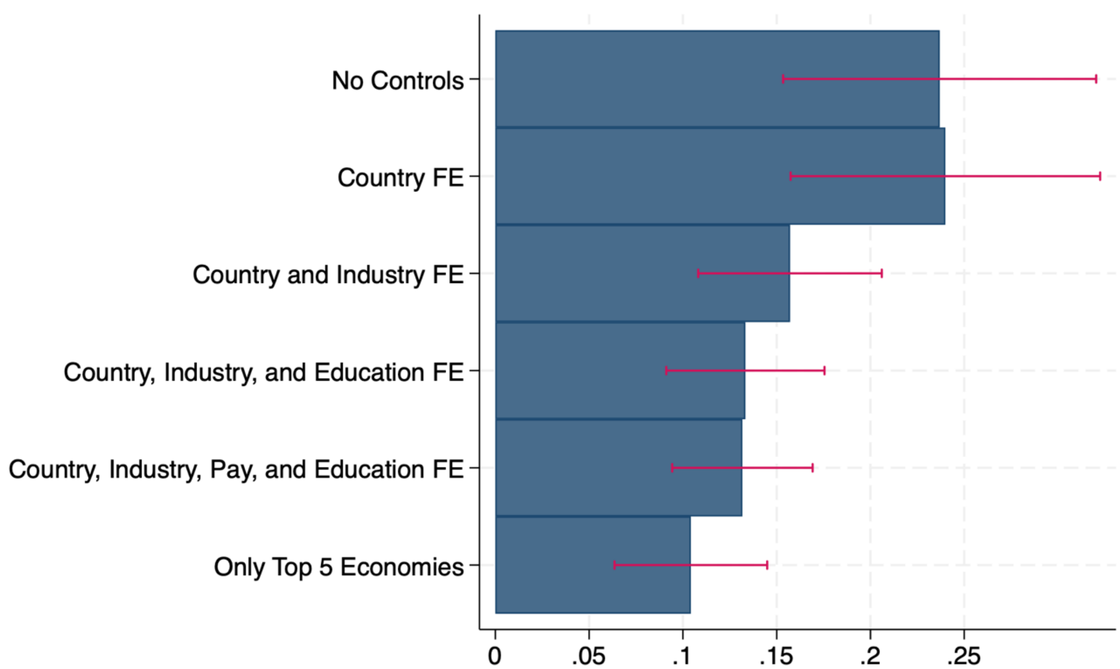
$$WFH_i = Teleworkable_j + \alpha_c + \alpha_s + \alpha_e + \alpha_y + \varepsilon_i, \qquad (1)$$

Where *WFH* is a dummy equal to one if the survey participant responds "yes" to the question described in Section 2.2. Teleworkable is a dummy equal to one if the participant is employed in a teleworkable occupation (indexed by *j*), according to the Dingel and Neiman (2020)'s taxonomy. The

α's represent vectors of fixed effects at the country (c), sector (s), education (e), and income (y) levels. Standard errors are clustered at the occupation level.

Before moving to the fully-fledged specification, we start by estimating a simple linear probability model with the teleworkability dummy as regressor and no other controls. As shown in Figure 36, we find that the probability of working remotely is 24 percentage points higher for workers in teleworkable occupations. The inclusion of country fixed effects has no effect on the estimate. Once we also include industry fixed effects, however, the coefficient drops to 0.16, suggesting that industry-level heterogeneity does explain a significant fraction of the occupational variation. However, the coefficient remains large and significant. Further including education and income level fixed effects only marginally reduces the size of the coefficient, which is now equal to 0.13. Finally, in the last row, we focus on the 5 largest economies in the sample, again using the most conservative specification. We find a coefficient equal to 0.10, again significant at the 1 percent level.

Figure 36: Work-from-Home and Teleworkable Occupations: OLS Regression Coefficients



Notes: This figure reports regression coefficients from OLS regressions where the dependent variable is a dummy equal to one if the survey participant who responds "yes" to the question "Compared with the situation before the Covid-19 pandemic, do you now experience any of the following situations in your main job? You work more time away from your employer's premises (e.g. remotely from home)." This dummy is regressed on a dummy equal to one if the worker is employed in a teleworkable occupation. Standard errors are clustered at the occupation level, defined using the 3-digit ISCO classification. The figure reports coefficients with 95% confidence intervals. Going from top to bottom, the specifications include: no controls; country fixed effects; country and industry fixed effects; country, industry, and education fixed effects; country, industry, pay, and education fixed effects; country, industry, pay, and education fixed effects for the five largest EU economies.

Overall, the evidence suggests that the teleworkability classification remains a strong predictor of actual work-from-home in a large sample of European countries, even after controlling for worker's observable characteristics.

2.4. Conclusion

We have shown that the probability of working from home is strongly related to the worker's occupation. Specifically, a simple binary "teleworkability" classification developed in an influential paper by Dingel and Neiman (2020) predicts a higher probability of working away from the employer's facilities after the pandemic. This pattern is present in a sample of workers surveyed by the ESJS, as well as in each of the five largest economies, with the partial exception of France. Moreover, the finding remains robust in a formal regression framework, where we account for heterogeneity with respect to countries, industry, education, and income.

This empirical exercise shows that the relationship between teleworkability and work-from-home is a feature of the labor market that extends beyond the Netherlands, validating the approach taken in the econometric analysis of the first chapter. Hence, our results are likely generalizable. Moreover, it shows that, while the pandemic has led to a dramatic shift in the labor market in terms of opportunities for teleworking, the availability of work-from-home arrangements are highly related to workers' occupations. Given that, as shown in the first chapter of this deliverable, teleworkability leads to more mobility and higher compensation, work-from-home may have important distributional effects, which should not be neglected by the policymakers.

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Appendix

Table 5: List of Non-Teleworkable Occupations

3-Digit Isco	Definition
111	Legislators and Senior Officials
131	Production Managers in Agriculture, Forestry and Fisheries
141	Hotel and Restaurant Managers
142	Retail and Wholesale Trade Managers
143	Other Services Managers
222	Nursing and Midwifery Professionals
225	Veterinarians
312	Mining, Manufacturing and Construction Supervisors
313	Process Control Technicians
314	Life Science Technicians and Related Associate Professionals
321	Medical and Pharmaceutical Technicians
322	Nursing and Midwifery Associate Professionals
324	Veterinary Technicians and Assistants
511	Travel Attendants, Conductors and Guides
512	Cooks
513	Waiters and Bartenders
515	Building and Housekeeping Supervisors
516	Other Personal Services Workers
523	Cashiers and Ticket Clerks
532	Personal Care Workers in Health Services
611	Market Gardeners and Crop Growers
613	Mixed Crop and Animal Producers
711	Building Frame and Related Trades Workers
712	Building Finishers and Related Trades Workers
721	Sheet and Structural Metal Workers, Moulders and Welders, and Related
722	Blacksmiths, Toolmakers and Related Trades Workers
723	Machinery Mechanics and Repairers
741	Electrical Equipment Installers and Repairers
742	Electronics and Telecommunications Installers and Repairers
751	Food Processing and Related Trades Workers
752	Wood Treaters, Cabinet-makers and Related Trades Workers
754	Other Craft and Related Workers
811	Mining and Mineral Processing Plant Operators
812	Metal Processing and Finishing Plant Operators
813	Chemical and Photographic Products Plant and Machine Operators
814	Rubber, Plastic and Paper Products Machine Operators
815	Textile, Fur and Leather Products Machine Operators
816	Food and Related Products Machine Operators
817	Wood Processing and Papermaking Plant Operators
818	Other Stationary Plant and Machine Operators
821	Assemblers
831	Locomotive Engine Drivers and Related Workers
832	Car, Van and Motorcycle Drivers
833	Heavy Truck and Bus Drivers
834	Mobile Plant Operators
835	Ships' Deck Crews and Related Workers

911	Domestic, Hotel and Office Cleaners and Helpers
912	Vehicle, Window, Laundry and Other Hand Cleaning Workers
921	Agricultural, Forestry and Fishery Labourers
931	Mining and Construction Labourers
932	Manufacturing Labourers
933	Transport and Storage Labourers
941	Food Preparation Assistants
952	Street Vendors (excluding Food)
961	Refuse Workers

Notes: This table presents the list of non-teleworkable occupations, defined using the 3-digit ISCO code classification, together with their definitions.

Table 6: List of Teleworkable Occupations

3-Digit Isco	Definition
112	Managing Directors and Chief Executives
133	Information and Communications Technology Service managers
212	Mathematicians, Actuaries and Statisticians
215	Electrotechnology Engineers
232	Vocational education teachers
233	Secondary Education Teachers
234	Primary School and Early Childhood Teachers
251	Software and Applications Developers and Analysts
262	Librarians, Archivists and Curators
332	Sales and Purchasing Agents and Brokers
334	Administrative and Specialized Secretaries
411	General Office Clerks
412	Secretaries (general)
413	Keyboard Operators
431	Numerical Clerks
531	Child Care Workers and Teachers' Aides

Notes: This table presents the list of teleworkable occupations, defined using the 3-digit ISCO code classification, together with their definitions.

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