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Remote Work and the Corporate Hierarchy

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Abstract

Using population-wide Finnish registry data linking an administrative measure of work from home (WFH) to matched employer-employee records, we study how the allocation of WFH across the corporate hierarchy relates to wages and firm performance. Although remote workers on average earn higher wages, job-to-job transitions into WFH show that this premium largely reflects selection and heterogeneity: managers experience wage declines of approximately 3%, while middle- and lower-layer workers experience no comparable declines. Firm-level evidence shows that the performance consequences of WFH depend on its hierarchical location. Greater lower-layer WFH penetration is associated with weaker performance, whereas managerial WFH is not associated with worse firm performance. Since managerial WFH is associated with wage declines without evidence of lower firm performance, we interpret the decline as a conservative lower bound on managers' valuation of WFH. Our results suggest that the value of WFH depends on where it is located inside the firm.

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"There are different kinds of jobs. Five days in the office for everybody is not going to happen again."

— James Gorman, then CEO of Morgan Stanley, January 2023

1. Introduction

Workplace flexibility has become a central organizational-design choice for firms. The widespread shift toward work from home (WFH) after the COVID-19 pandemic not only changed where employees perform their tasks, but also how firms monitor workers, coordinate teams, and compensate employees. Roughly one quarter of paid workdays in advanced economies are now performed away from the employer's worksite, and remote work has become an important determinant of job choice, worker retention, and compensation design (Barrero, Bloom, and Davis, 2023).[1] Yet, firms not only choose the average level of remote work within the firm, they also choose where remote work is allocated along the corporate hierarchy. This allocation may matter for firm value because workers along the hierarchy perform different functions and may generate different costs and benefits when working remotely.

This distinction is important for corporate finance. Hierarchies allocate decision rights, information, monitoring responsibilities, and coordination tasks inside firms (Ewens and Giroud, 2025).[2] Remote work by managers may allow firms to attract and retain talent by partly compensating managers through workplace flexibility rather than cash wages, consistent with the logic of compensating differentials for workplace amenities.[3] It may also improve managerial surplus by reducing commuting costs and increasing autonomy. Conversely, because managers coordinate production, transmit information, and monitor other employees, remote managerial work could weaken communication, mentoring, and control. Remote work by lower-layer employees may also have different implications, especially when tasks require physical presence, close supervision, or team production. Thus, the value of WFH may depend less on how much remote work a firm adopts than on where remote work is located within the firm.

In this paper, we study remote work as an organizational-design choice using Finnish population-wide registry data. Our data link a direct tax-based measure of high-intensity WFH to matched

[1] Academic interest in remote work has also grown rapidly, with more than 1% of NBER working papers released in 2025 containing either "remote work" or "work from home" in the abstract (Goldsmith-Pinkham, 2024).

[2] See also Garicano (2000) and Rajan and Wulf (2006).

[3] See, among others, Mas and Pallais (2017), Aksoy et al. (2022), Bartik, Cullen, Glaeser, Luca, and Stanton (2025), Cullen, Pakzad-Hurson, and Perez-Truglia (2025), De Fraja et al. (2025), and Dias da Silva and Weissler (2025).

employer-employee records, occupational codes, worker characteristics, and firm financial statements. This setting offers several advantages. First, we observe remote work uptake at the individual-year level rather than relying on survey responses, job postings, selected samples, or firm-level policies. Our WFH measure is population-wide, longitudinal, and highly correlated with the teleworkability scores developed by Dingel and Neiman (2020).[4] Second, we can assign workers to broad hierarchical layers within firms (Caliendo, Monte, and Rossi-Hansberg, 2015). Third, because the worker-level records are linked to firm financial statements, we can jointly study how remote work is priced in wages and how its allocation across the hierarchy relates to subsequent firm performance. Finally, Finland is among the most remote work intensive economies in the world, providing substantial variation in remote work adoption both across and within firms (Gill, Hensvik, and Skans, 2025).

We ask two related questions. First, how is WFH priced in wages across different layers of the corporate hierarchy? This question speaks to the literature on compensating differentials and the worker valuation of remote work. Survey and experimental studies estimate that workers are willing to forgo meaningful amounts of pay for remote work or flexible work arrangements (Mas and Pallais, 2017; Aksoy et al., 2022; Bartik, Cullen, Glaeser, Luca, and Stanton, 2025; Cullen, Pakzad-Hurson, and Perez-Truglia, 2025; De Fraja et al., 2025). Administrative data, however, show that remote workers earn higher wages, consistent with positive selection into remote jobs (Li, Sauvagnat, and Schmitz, 2026).

Second, conditional on a firm's overall remote work adoption, does the hierarchical allocation of WFH affect firm performance? This question is connected to a strand of literature that examines the consequences of remote work for firms. Using a pre-pandemic sample ending in 2019, Duchin and Sosyura (2025) document that remote work arrangements between CEOs and their firms are associated with worse firm performance. Other recent work finds mixed evidence on the firm-level effects of remote work, suggesting that heterogeneity may play an important role (e.g., Kwan, Matthies, and Yuskavage, 2025; Gupta, Gupta, and Simintzi, 2026).

Although the prior literature has considered these two questions separately, we begin with a simple framework that illustrates why the firm-level performance implications of remote work are necessary for guiding the interpretation of the wage effects of WFH. In particular, since the observed wage effects of WFH combine a productivity or surplus component, which may increase wages through

[4] Throughout the paper, we refer to high-intensity remote work as "remote work" or "work from home." We provide a detailed description of our measure in Section 3 of the paper.

rent sharing, and an amenity component, which may reduce wages if workers value the flexibility of remote work, wages alone cannot disentangle these two forces and determine how workers value WFH. However, by combining worker-side wage estimates with firm-side performance estimates, we can determine that if workers in a given layer experience wage declines when moving into WFH and firm-side performance does not deteriorate when WFH rises in that layer, then the wage decline has a natural interpretation as a conservative lower bound on workers' valuation of WFH. Studying the wage and firm performance effects of WFH jointly thus allows us to pin down how workers value WFH in a way that studying wages in isolation would not.

Our worker-level analysis exploits job-to-job transitions. We compare workers who leave the same origin firm in the same year but move to destination jobs that differ in remote work adoption. The empirical design follows the logic of matched-mover designs that use worker mobility to separate worker heterogeneity from firm or job characteristics (Card, Heining, and Kline, 2013). The pooled worker-level results show that remote workers earn more on average, but this premium largely reflects selection. Once we allow the wage effect of WFH to vary across the corporate hierarchy, we find that managers who move into remote jobs experience wage declines of approximately 3% in our most demanding specifications. By contrast, middle- and lower-layer workers experience wage changes close to zero. The pooled wage effect thus masks substantial heterogeneity across layers. Remote work appears to be priced differently for managers than for the rest of the workforce.

We then turn to firm-level evidence. We first show that aggregate firm-wide WFH intensity is not strongly related to subsequent firm performance. However, this near-zero average association again masks substantial heterogeneity across the hierarchy. When we decompose WFH by layer, we find that lower-layer WFH is negatively associated with ROA, whereas managerial WFH is not associated with worse firm performance. These patterns are consistent with recent evidence that the firm-level effects of remote work are heterogeneous and depend on organizational context, technology, and managerial practices (e.g., Boeri, Crescenzi, and Rigo, 2025).

Our main firm-level specification asks whether the allocation of WFH matters conditional on the total amount of WFH in the firm. We define WFH skew as the difference between upper-layer WFH and lower-layer WFH. Across demanding fixed effect specifications, we find that WFH skew is positively associated with subsequent ROA, while overall WFH intensity remains small and statistically insignificant. In other words, for a given level of remote work, firms where WFH is more concentrated in the lower layer tend to exhibit weaker subsequent performance.

We complement these OLS results with an instrumental variables strategy based on firms' pre-pandemic occupational composition, interacted with occupation-level changes in WFH during the onset of the COVID-19 pandemic. The instruments exploit the fact that firms with greater pre-pandemic exposure to occupations that became more remote work intensive during the pandemic experienced larger shifts in WFH. The IV estimates confirm that WFH skew is positively related to subsequent performance. We interpret this evidence as supportive rather than definitive, because pre-pandemic occupational composition may also be correlated with other pandemic-era shocks. Nevertheless, the IV results reinforce the central conclusion that the allocation of remote work across the hierarchy is more informative for firm performance than aggregate WFH intensity alone.

Combining the worker- and firm-level evidence yields an asymmetric interpretation across hierarchical layers. For managers, we estimate a negative wage effect of moving into remote work and find no evidence that managerial WFH worsens firm performance. Under the sign restriction that managerial WFH does not reduce firm-side surplus, the managerial wage decline provides a conservative lower bound on the compensating differential for WFH. The estimated lower bound is approximately 3%. For other layers, we are unable to identify bounds for the compensating differential for WFH using our framework.

This paper contributes to several strands of literature. First, we add to the growing literature on the corporate consequences of remote work (Kwan, Matthies, and Yuskavage, 2025; Boeri, Crescenzi, and Rigo, 2025; Gupta, Gupta, and Simintzi, 2026). We show that remote work has different effects depending on where in the corporate hierarchy it is allocated. Our results complement the evidence of Duchin and Sosyura (2025) by focusing on broad layer-specific remote work allocation in a post-pandemic regime rather than on CEO-level remote leadership in a pre-pandemic regime.

Second, we contribute to the literature on the worker valuation of remote work (e.g., Mas and Pallais, 2017; Aksoy et al., 2022; Cullen, Pakzad-Hurson, and Perez-Truglia, 2025; Li, Sauvagnat, and Schmitz, 2026). We show that the apparent tension between the survey-based finding that workers are willing to pay for remote work and the administrative data finding that remote workers earn higher wages can be partly reconciled once one accounts for hierarchical heterogeneity. Within demanding job-mover specifications, the wage data are consistent with a meaningful compensating differential for managers and a near-zero differential for the rest of the workforce, even though the average remote worker continues to earn a wage premium driven by selection. Methodologically, our paper is also the first, to our knowledge, to combine a direct, population-wide administrative measure of remote work with a firm-side moment that allows us to provide evidence on whether the non-wage firm-side consequences of remote work are positive or negative.

Third, we add to a broad literature on corporate hierarchy (e.g., Caliendo, Monte, and Rossi-Hansberg, 2015; Caliendo, Mion, Opromolla, and Rossi-Hansberg, 2020; Ewens and Giroud, 2025) by examining its relation with remote work. Our paper documents that the economic consequences of remote work are fundamentally organizational. These consequences do not depend primarily on the aggregate prevalence of remote work within a firm, but rather on where remote work is located along the corporate hierarchy.

2. Stylized Framework

This section presents a simple decomposition that motivates our joint analysis of wages and firm performance. Its purpose is to clarify when the observed wage effect of remote work can be interpreted as a compensating differential and to show why firm-level evidence is essential for that interpretation.

Suppose that workers in layer $\ell \in \{U, M, L\}$ value WFH at δ_ℓ in wage-equivalent units, that WFH shifts pre-wage match productivity in layer ℓ by μ_ℓ, and that wages share match surplus with the worker's proportion denoted by $\sigma_\ell \in [0, 1)$. Under a standard rent-sharing logic, it follows that the wage effect of WFH in layer ℓ, denoted by β^w_ℓ, can be decomposed as

$$\beta^w_\ell \;=\; \sigma_\ell \mu_\ell \;-\; (1 - \sigma_\ell)\, \delta_\ell. \tag{1}$$

Equation (1) illustrates the key obstacle to identifying the compensating differential. While a negative wage effect ($\beta^w_\ell < 0$) may reflect a compensating differential ($\delta_\ell > 0$), it may also reflect a movement into lower-surplus matches ($\mu_\ell < 0$). Conversely, a positive wage effect may reflect productivity gains shared with workers rather than the absence of an amenity value. Wages alone thus cannot separate the productivity component μ_ℓ from the amenity component δ_ℓ.

To overcome this problem, we use firm performance as a complementary firm-side moment. Let β^π_ℓ denote the response of firm performance to layer-ℓ WFH adoption. This coefficient is not a direct measure of the pre-wage match productivity effect μ_ℓ since accounting performance is observed net of wages and may also reflect other costs or organizational changes associated with remote work. Nevertheless, it is informative about the sign of the firm-side surplus generated by WFH. In particular, the mechanical wage-savings channel is small in our setting, with its contribution to firm performance being approximately $-\beta_\ell^w$ times the ratio of the layer-ℓ wage bill to total assets. With wage effects on the order of a few percent and wage bills that are a fraction of total assets, this mechanical contribution is an order of magnitude smaller than the firm-performance responses we estimate. We therefore interpret the sign of β_ℓ^π not as directly identifying μ_ℓ, but as providing evidence on whether the non-wage firm-side consequences of WFH are positive or negative, and hence on the plausibility of the sign restriction on μ_ℓ.

Combining the worker- and firm-level estimates allows us to derive a conditional lower-bound interpretation of the compensating differential. Suppose $\beta_\ell^w < 0$ and $\beta_\ell^\pi \geq 0$, so that wages fall while firm-side surplus is non-negative. The latter is consistent with $\mu_\ell \geq 0$, and Equation (1) then implies:

$$\delta_\ell \;=\; \frac{\sigma_\ell \mu_\ell - \beta_\ell^w}{1-\sigma_\ell} \;\geq\; \frac{-\beta_\ell^w}{1-\sigma_\ell} \;\geq\; -\beta_\ell^w. \tag{2}$$

The intuition is straightforward. If WFH weakly increases pre-wage productivity, then rent-sharing would push wages up. Observing a decrease in wages despite this force implies that workers value WFH by at least the amount of the wage decline.

3. Data

3.1 Identifying Layers

We measure employees' hierarchical rank within the firm using occupational codes provided by Statistics Finland. This procedure follows a simplified version of the method in Caliendo, Monte, and Rossi-Hansberg (2015) for identifying layers within organizations.[5] A layer is a group of employees who have similar knowledge levels and wages and who perform tasks at a similar level of authority. Layers are hierarchical in that the typical worker in a higher layer earns more. Using the classification of occupations used by Statistics Finland, we split workers into three main layers, listed in hierarchical order: upper layer (i.e., managers), middle layer, and lower layer.[6]

[5] In recent work, Hvide and Nielsen (2026) use occupational codes to identify managers below the top in Norway.

[6] The layers reflect the first digit of the occupational codes used by Statistics Finland. The codes are guided by a hierarchical classification system known as International Standard Classification of Occupations, created by the International Labour

3.2 Worker-Level Data

Next, we present and describe our worker-level data.

3.2.1 Worker-Level Data on Remote Work Uptake

Our information on remote work uptake originates from tax reports and is therefore measured at the individual-year level between 2018 and 2023. We obtain the information from Statistics Finland, which in turn receives it from the Finnish Tax Administration (FTA).

Contrary to several other Western countries, Finnish taxpayers can access and modify their tax reports free of charge either in person or online via the MyTax service, available on the website of the FTA. These services are easily and readily available to Finnish taxpayers. For example, during the calendar year 2023, there were 33.5 million logins to the MyTax service.[7] While the FTA provides Finnish taxpayers with pre-completed tax returns, taxpayers can easily modify these documents online, for example by claiming additional deductions. In 2023, 1.5 million individual taxpayers made changes to their pre-completed tax returns.[8]

During our sample period, these deductions include a specific "home office deduction." Figure 1 reports a screenshot from the MyTax service, showing how taxpayers are actively prompted to select the fraction of days they worked from home in order to claim the corresponding home office deduction. Specifically, if taxpayers work from their own home, they can deduct their expenses in one of two ways. 98.5% of taxpayers claiming a home office deduction for fiscal year 2023 opt for a formula-based home office deduction. In other words, taxpayers can select whether they worked from home for more than 50% of all their working days in the calendar year, for no more than 50% of their working days, or just for the production of occasional secondary income. The three options are associated with different amounts of home office deductions, respectively €940, €470, and €235.[9] A small minority (1.5%) of taxpayers claiming a home office deduction opt to use their actual expenses

Organization. The scale includes managers (occupational code 1), professionals (2), technicians and associate professionals (3), clerical and support workers (4), service and sales workers (5), skilled agricultural/forestry/fishery workers (6), craft and related trades workers (7), plant and machine operators/assemblers (8), and elementary occupations (9). We exclude armed forces (occupational code 0) and aggregate one-digit occupational codes 2 through 3 and 4 through 9.

[7] See https://web.archive.org/web/20240612182525/https://www.vero.fi/en/About-us/finnish-tax-administration/finnish-tax-administrations-year/positive-customer-experience/.

[8] For reference, as of 2023, Finland had a total population of approximately 5.6 million individuals, of which 2.4 million were employed (see https://stat.fi/en/publication/clmfzjgqssf4i0bw615katggs).

[9] Small changes in the exact euro amounts occur during our sample period. Euro amounts in this section refer to fiscal year 2023. For additional details as of July 2024, see https://web.archive.org/web/20240717140434/https://www.vero.fi/en/individuals/deductions/expenses-for-the-production-of-income/home-office-deduction/.

incurred while working from home.

Importantly, the home office deduction is included among a broader category of expenses for the production of income, which covers all costs incurred from the generation of wage income. All wage income earners in Finland automatically receive a €750 deduction for the production of income. Thus, taxpayers who report expenses for the production of income only gain additional monetary benefit if these expenses exceed the €750 threshold. In other words, taxpayers who work from home for no more than 50% of their working days (or only for the production of occasional secondary income), and who have no other large expenses for the production of income (e.g., computers, data connections, tools, training expenses), have no financial incentives to claim the formula-based home office deduction. On the contrary, taxpayers who report working from home for more than 50% of their working days benefit by a net amount equal to their marginal tax rate multiplied by €190 (=€940-€750), regardless of whether they had additional expenses for the production of income.[10] Consistent with these economic incentives, approximately 85% of taxpayers claiming a formula-based home office deduction in 2023 declare that they work from home for more than 50% of all their working days. For these reasons, our operational definition of remote work is whether someone reports "more than 50% of work days working from home."[11] Reassuringly, this 50% cutoff represents a long-standing, well-established threshold for the definition of high-intensity telecommuting (e.g., Gajendran and Harrison, 2007). For simplicity, throughout the paper, we refer to this high-intensity telecommuting classification as "remote work" or "work from home."

While the measure is self-reported, Finland is a high-trust country, and tax evasion remains a limited phenomenon. For example, a 2025 survey reveals that 93% of Finns think paying taxes is an important civic duty, and 85% believe that tax evasion is always wrong (Verohallinto, 2025). Moreover, the economic incentive to misreport is relatively small (less than €10 per month after taxes even for taxpayers with the highest marginal tax rate). Appendix B reports extensive validation tests of our measure of remote work.

[10]Expenses for the production of income are subtracted from one's income before the calculation of tax. In other words, these expenses reduce the amount of income subject to tax, which indirectly reduces the total amount of tax.

[11]To take into account reporting incentives, we also classify as working from home those who claim a home office deduction using actual expenses when these expenses exceed the highest formula-based threshold set by the FTA for that fiscal year.

3.2.2 Other Worker-Level Data

Most other worker-level data come from ready-made modules provided by Statistics Finland. We observe annual worker-level measures of wages, occupations, demographic characteristics, family background, and education.[12] We also build on Dingel and Neiman (2020) and include a country-specific measure of teleworkability for occupations identified at the 2-digit major-group level (for more details, see Appendix B).

3.2.3 Worker-Level Summary Statistics

Panel A of Table 1 reports worker-level summary statistics for the sample used in the individual-level analyses. The final sample contains 1,168,899 worker-year observations.[13] Average annual wage income amounts to €49,334, although the distribution is substantially dispersed, with a standard deviation of €34,856 and an interquartile range between €34,045 and €55,602. The average worker is 42 years old, 41.7% of the sample is female, 46.5% are married, and 40.8% hold a university degree.

The layer composition of the workforce shows that 3.6% of employees belong to the upper layer, 45.1% to the middle layer, and 51.3% to the lower layer. The average teleworkability score equals 0.41, with substantial heterogeneity across occupations. The median teleworkability score of 0.32 further suggests that many occupations in the sample remain only partially compatible with remote work arrangements.

Approximately 10.1% of worker-year observations are classified as high-intensity remote work, indicating that remote work remains concentrated among a relatively limited subset of employees in the sample. Figure 2 further illustrates the evolution of remote work over time, showing a sharp increase during the COVID-19 pandemic followed by a gradual normalization in subsequent years, with upper and middle-layer workers having higher rates of remote work than lower-layer workers.

Overall, the descriptive statistics indicate that remote work adoption is unevenly distributed across workers, occupations, and time, motivating our subsequent focus on organizational hierarchy and occupational characteristics as key determinants of remote work uptake and its economic consequences.

[12] Throughout the paper, all continuous variables are winsorized at the 0.5% and 99.5% levels.

[13] The summary statistics in Table 1 are computed on the analysis sample; the number of observations reported in the regression tables is smaller because some observations are dropped when absorbing high-dimensional fixed effects.

3.3 Firm-Level Data

Firm-level measures are obtained directly from Statistics Finland and are available through 2024. We only include private firms, and exclude firm-years and sectors flagged by Statistics Finland as having unreliable data.[14]

3.3.1 Firm-Level Summary Statistics

Panel B of Table 1 reports firm-level summary statistics for the sample used in the firm-level analyses. The sample consists of firm-year observations covering the period from 2019 to 2024. The descriptive statistics indicate substantial heterogeneity across firms in terms of size, profitability, leverage, and remote work adoption.

The distribution of remote work across firms also varies substantially by organizational layer. While remote work adoption increased markedly during and after the COVID-19 pandemic, Figure 2 suggests that the intensity of adoption differed systematically across the hierarchy, with upper- and middle-layer occupations displaying persistently higher levels of remote work than lower-layer occupations. The firm-level statistics therefore reinforce the worker-level evidence that remote work is unevenly distributed across organizations and occupational ranks. This heterogeneity motivates the subsequent empirical analysis examining whether remote work adoption across hierarchical layers is associated with differences in firm performance.

4. Methodology

Below, we discuss the empirical approach for our worker-level and firm-level analyses.

4.1 Worker-Level Methodology

Our identification strategy leverages job-to-job transitions and granular fixed effects to compare similar workers who accept jobs that differ in WFH intensity. Our sample consists of all workers in Finland who work for two employers between 2018 and 2023, and who did not work remotely with

[14] The excluded sectors include primary production, financial intermediation, public administration and defence, public education units, activities of organisations, extra-territorial organizations and bodies, unknown and empty industries, and activities of holding companies.

their origin employer.[15]

We implement this strategy through an event-study specification:

$$\ln(y_{i,c,t}) = \sum_{\tau \neq -1} \beta_\tau \cdot \mathbb{1}(t - T_{i,c} = \tau) \cdot \mathbb{1}(GainWFH_i = 1) + \gamma X_{i,t} + \delta_i + \theta_{c,t} + \eta_{j_1,t} + \zeta_{j_2,t} + \pi_{o_1,o_2} + \varepsilon_{i,c,t}, \tag{3}$$

where the dependent variable is the annual wage and salary earnings of worker i in year t and $T_{i,c}$ is the year in which worker i switches from employer j_1 to employer j_2, so that $t - T_{i,c} = \tau$ indexes event time relative to the move, with $\tau = -1$ omitted as the reference period. $\mathbb{1}(t - T_{i,c} = \tau)$ indicates event time, with c indexing the cohort of workers who change employer in a given year. $\mathbb{1}(GainWFH = 1)$ equals one if worker i moves into a high-intensity WFH job, and zero otherwise. $X_{i,t}$ are worker-level control variables such as age and its square.

The coefficients β_τ trace the differential earnings trajectory of workers who move into high-WFH jobs relative to comparable movers who do not, normalized to the year before the move. Note that the cohort-by-year fixed effects ($\theta_{c,t}$) mechanically absorb event time because τ is a linear function of t within each cohort. Thus, the identification of β_τ comes entirely from the interaction with $\mathbb{1}(GainWFH = 1)$, that is, from the differential trajectory of WFH-gainers relative to non-WFH movers within the same cohort-year. The identifying assumption is that, absent the transition into a high-WFH job, WFH gainers and non-WFH movers within the same comparison cells would have followed parallel earnings trajectories.

We make extensive use of fixed effects. δ_i are worker fixed effects that absorb time-invariant worker heterogeneity. $\theta_{c,t}$ are job-change-cohort $\times$ year fixed effects that flexibly control for cohort-specific time paths. $\eta_{j_1,t}$ are origin-firm-by-year fixed effects (j_1 denotes the worker's origin employer), absorbing common wage premia and local labor market conditions among workers leaving the same firm in the same year. $\zeta_{j_2,t}$ are destination-firm-by-year fixed effects (j_2 denotes the worker's destination employer), which absorb most of the wage premium specific to the destination firm. Finally, π_{o_1,o_2} are origin occupation $\times$ destination occupation fixed effects controlling for occupation-specific wages.

Since we are particularly interested in the allocation of remote work across the organizational hierarchy, we also augment Equation (3) to identify how the wage changes associated with switching

[15] Our sample restriction is in the spirit of Card, Heining, and Kline (2013), who require workers to have held the preceding job for two or more years, and the new job for two or more years in their mover event study. This restriction is what cleanly identifies the effect of a job switch on outcomes, since expected wage growth depends entirely on the change in destination effects associated with the worker's job transition.

to remote jobs vary across layers. We classify each worker's origin occupation into one of three hierarchical layers — upper (managers), middle, and lower — and interact event time with both layer indicators and the *GainWFH* indicator. Taking the upper layer as the omitted baseline, our specification is:

$$
\begin{aligned}
\ln(y_{i,c,t}) = & \sum_{\tau\neq-1} \beta_\tau \cdot \mathbb{1}(t - T_{i,c} = \tau) \cdot \mathbb{1}(\text{GainWFH}_i = 1) + \\
& + \sum_{\ell\in\{M,L\}} \sum_{\tau\neq-1} \beta^{\ell}_{\tau} \cdot \mathbb{1}(t - T_{i,c} = \tau) \cdot \mathbb{1}(\text{Layer}_i = \ell) + \\
& + \sum_{\ell\in\{M,L\}} \sum_{\tau\neq-1} \beta^{\ell W}_{\tau} \cdot \mathbb{1}(t - T_{i,c} = \tau) \cdot \mathbb{1}(\text{Layer}_i = \ell) \cdot \mathbb{1}(\text{GainWFH}_i = 1) + \\
& + \gamma X_{i,t} + \delta_i + \theta_{c,t} + \eta_{j_1,t} + \zeta_{j_2,t} + \pi_{o_1,o_2} + \varepsilon_{i,c,t},
\end{aligned}
\tag{4}
$$

where $\text{Layer}_i \in \{U, M, L\}$ denotes the worker's origin-occupation layer (upper, middle, or lower), with the upper layer omitted as the baseline. Our objects of interest are the dynamic wage effects of moving into a high-WFH job within each layer. For upper-layer workers, this effect is given directly by β_τ. For middle- and lower-layer workers, the corresponding effect is given by the sum $\beta_\tau + \beta^{\ell W}_{\tau}$, where $\beta^{\ell W}_{\tau}$ captures the differential wage effect of gaining WFH for layer $\ell \in \{M, L\}$ relative to the upper layer.[16]

4.2 Firm-Level Methodology

We begin by estimating a baseline firm-level specification that relates firm performance to lagged remote work adoption at the firm level, without distinguishing across organizational layers:

$$
ROA_{j,t} = \beta_1 WFH_{j,t-1} + \theta X_{j,t-1} + \gamma_{s,t} + \delta_j + \varepsilon_{j,t}, \tag{5}
$$

where j indexes firms and t indexes years. The dependent variable is return on assets, defined as net income divided by the book value of total assets following Duchin and Sosyura (2025). The variable $WFH_{j,t-1}$ measures overall remote work adoption in firm j in the previous year. The vector $X_{j,t-1}$ includes lagged firm-level controls. $\gamma_{t,s}$ and δ_j denote industry-by-year and firm fixed effects, respectively. The industry-by-year fixed effects absorb shocks common to all firms in the same

[16] The coefficients β^{ℓ}_{τ} are not of direct interest. They flexibly absorb layer-specific event-time earnings trajectories common to WFH-gainers and non-gainers.

industry in a given year (e.g., industry-wide demand, technology, or pandemic-related disruptions), so that identification comes from within-industry-year differences across firms. The firm fixed effects absorb time-invariant firm heterogeneity, such as persistent differences in business model, location, or management quality. The control variables include a startup indicator (Gupta, Gupta, and Simintzi, 2026), lagged ROA, lagged leverage, lagged log assets, and the lagged number of employees. Leverage is defined as total liabilities divided by total assets.

We then extend the analysis by decomposing firm-level remote work adoption across organizational layers. This allows us to examine whether remote work in different parts of the hierarchy has differential consequences for firm performance. Our primary layer-specific specification relates firm performance to lagged remote work adoption in the upper, middle, and lower layers of the firm:

$$ROA_{j,t} = \beta_1 WFH^{upper}_{j,t-1} + \beta_2 WFH^{middle}_{j,t-1} + \beta_3 WFH^{lower}_{j,t-1} + \theta X_{j,t-1} + \gamma_{s,t} + \delta_j + \varepsilon_{j,t}, \quad (6)$$

where $WFH^{upper}_{j,t-1}$, $WFH^{middle}_{j,t-1}$, and $WFH^{lower}_{j,t-1}$ measure remote work adoption in the upper, middle, and lower layers of firm j, respectively.

We further extend our analysis to examine whether, conditional on a given level of remote work within the firm, its allocation across layers matters. To do so, we use the following specification:

$$ROA_{j,t} = \beta_1 WFH_{j,t-1} + \beta_2 WFHSkew_{j,t-1} + \theta X_{j,t-1} + \gamma_{s,t} + \delta_j + \varepsilon_{j,t}, \quad (7)$$

where $WFH_{j,t-1}$ measures overall remote work adoption in firm j in the previous year, and $WFHSkew_{j,t-1}$ is the difference between upper-layer WFH and lower-layer WFH.

We consider Equation (7) to be the primary specification for our firm-level tests, since it answers a very fundamental question: for a given level of remote work, does its allocation within a firm matter for firm performance? However, a concern with estimating Equation (7) using OLS is that remote work adoption may be endogenous. For example, firms with better unobserved management practices may both adopt remote work more effectively and subsequently perform better. Conversely, firms facing negative shocks may turn to remote work as a cost-saving or restructuring strategy. To partially address this concern, we use an instrumental variables strategy based on firms' pre-pandemic occupational composition interacted with occupation-level changes in remote work during the onset of the pandemic.

For each organizational layer $\ell \in \{upper, middle, lower\}$, we construct an instrument $Z^{\ell}_{j,2019,2020}$ that combines firm j's pre-pandemic occupational composition in layer ℓ with leave-one-out occupation-level changes in remote work adoption from 2019 to 2020. Specifically, the instrument exploits the fact that firms with a larger pre-pandemic employment share in occupations that became more remote work intensive during the pandemic were more exposed to the remote work shock. We use granular four-digit occupational codes, and the leave-one-out construction excludes firm j when calculating occupation-level changes in remote work.

The first-stage equations are:

$$\begin{aligned} WFH_{j,t-1} = {} & \pi_1 Z^{upper}_{j,2019,2020} \times Post_{t-1} + \pi_2 Z^{middle}_{j,2019,2020} \times Post_{t-1} + \pi_3 Z^{lower}_{j,2019,2020} \times Post_{t-1} \\ & + \theta' X_{j,t-1} + \gamma'_{s,t} + \delta'_j + u'_{j,t-1}, \end{aligned} \tag{8}$$

$$\begin{aligned} WFHSkew_{j,t-1} = {} & \rho_1 Z^{upper}_{j,2019,2020} \times Post_{t-1} + \rho_2 Z^{middle}_{j,2019,2020} \times Post_{t-1} + \rho_3 Z^{lower}_{j,2019,2020} \times Post_{t-1} \\ & + \theta'' X_{j,t-1} + \gamma''_{s,t} + \delta''_j + u''_{j,t-1}. \end{aligned} \tag{9}$$

Here, $Post_{t-1}$ is an indicator equal to one for years in which the lagged remote work measure refers to 2020 or later, and zero otherwise. Because the specification includes firm fixed effects and industry-by-year fixed effects, identification comes from differential post-pandemic exposure to occupations with greater remote work potential, conditional on time-invariant firm heterogeneity, aggregate industry-level year shocks, and lagged firm characteristics.

The corresponding second-stage equation is:

$$ROA_{j,t} = \beta_1 \widehat{WFH}_{j,t-1} + \beta_2 \widehat{WFHSkew}_{j,t-1} + \theta X_{j,t-1} + \gamma_{s,t} + \delta_j + \varepsilon_{j,t}. \tag{10}$$

The exclusion restriction is that, conditional on firm fixed effects, industry-by-year fixed effects, and lagged firm-level controls, the interaction between a firm's pre-pandemic occupational composition and leave-one-out occupation-level changes in remote work affects subsequent firm performance only through its effect on the firm's own adoption of remote work in the corresponding organizational layers. In other words, the instruments must not affect $ROA_{j,t}$ through other channels, such as occupation-specific demand shocks, changes in technology adoption unrelated to remote work, or differential exposure to pandemic-era disruptions, except insofar as these channels operate through remote work adoption. The leave-one-out construction helps address mechanical reflection concerns by ensuring that the occupation-level remote work shock used to instrument firm j's remote work adoption is not driven by firm j's own change in remote work. A potential concern is that occupations experiencing larger increases in remote work during the pandemic may also have been differentially exposed to other shocks, such as changes in demand, digitalization, or broader technological transformations. While these concerns cannot be ruled out entirely, we address them in more detail in Section 6.

5. Worker-Level Results

Below, we present our worker-level results. First, we pool all workers together. Then, we focus on the effect of hierarchy.

5.1 Pooled Worker-Level Results

We begin with the pooled estimates from Equation (3), which compare workers who move into high-intensity remote jobs with comparable movers who remain in on-site jobs. Figure 3 plots the event-study coefficients, and Appendix Table A1 reports the corresponding regression estimates. Columns 1-4 follow a deliberate tightening sequence: unrestricted movers, same three-digit occupation movers, same three-digit occupation movers with high-teleworkability occupations, and then the same narrow sample with additional occupation-by-year and region-by-year fixed effects. Across specifications, the estimates trace the differential earnings path of remote work gainers relative to the year before the job change ($\tau = -1$). Because job changes typically occur partway through the calendar year, the coefficient at $\tau = 0$ (i.e., the year of the move) is potentially contaminated by partial-year employment, timing of wage resets at hire, and other transitory factors tied to the transition itself. We therefore focus on $\tau = 1$ as our preferred post-move benchmark.

In the least restrictive specification (Column 1 of Table A1), workers who transition into remote jobs experience statistically significant wage increases in the years following the move, with a wage gain of approximately 1.3%. These pooled estimates are consistent with the positive wage gap between remote and on-site workers documented in administrative data (Li, Sauvagnat, and Schmitz, 2026). However, the positive effects attenuate as we tighten the comparison set. When we restrict the sample to movers who remain in the same three-digit occupation (Column 2), to occupations with high teleworkability (Column 3), and finally add occupation-by-year and region-by-year fixed effects (Column 4), the post-move wage gains shrink. In our most demanding specification, the wage effect at $\tau = 1$ is small and not statistically different from zero. Figure 3 makes this pattern transparent: the confidence intervals widen and the post-move coefficients move toward zero (and, at longer horizons, below zero) as the sample restrictions and fixed effects tighten.

This erosion of the pooled wage premium is informative about the role of selection. Workers who move into remote jobs differ along dimensions that are only partly absorbed by worker, cohort, firm, and origin-by-destination occupation fixed effects. Restricting to within-occupation moves and high-teleworkability occupations removes a substantial share of compositional differences between remote and on-site destinations. The remaining positive pooled estimates in less demanding specifications therefore likely reflect, at least in part, sorting of higher-earning workers into remote positions rather than the pricing of remote work as a compensating amenity.

5.2 Worker-Level Results Across the Organizational Hierarchy

We next turn to heterogeneity across the organizational hierarchy using Equation (4). As in the pooled analysis, Columns 1-4 should be read as progressive tightening of comparability: unrestricted movers, same three-digit occupation movers, same three-digit occupation movers within high-teleworkability occupations, and then the inclusion of occupation-by-year and region-by-year fixed effects on the same restricted sample.

Figure 4 reports layer-specific dynamic wage effects, and Appendix Table A2 reports the underlying coefficients. Our headline estimate is the most demanding specification: at $\tau = 1$, upper-layer workers who move into remote jobs experience a statistically significant wage decline of approximately 3%. In this design, the comparison is among managers who remain in the same layer, move within the same three-digit occupation, are observed in high-teleworkability occupations, and are compared within a rich fixed effects structure. The decline further deepens over time, reaching -5.7% at $\tau = 4$. Pre-treatment coefficients for upper-layer remote work gainers are generally small and insignificant in more demanding specifications.

For middle-layer workers, the post-move trajectory differs markedly from that of managers. In

Column 4, the net wage effect of moving into a remote job is close to zero throughout the post-move window. At $\tau = 1$, the estimates are generally economically very small. Panel B of Figure 4 shows no sustained negative wage path for middle-layer gainers once the same occupation, teleworkability, and additional fixed effect restrictions are imposed.

Panel C of Figure 4 shows that lower-layer workers generally experience wage increases when moving into remote jobs, but the magnitude of these gains depends on the specification. In the unrestricted subsample, post-move coefficients lie above zero at every horizon from $\tau = 0$ onward. As we restrict the comparison set, the point estimates attenuate and the confidence intervals widen, so that the post-move gains are no longer uniformly statistically significant. Lower-layer workers therefore do not exhibit the sustained wage declines seen among managers, but the positive wage effects visible in less restrictive designs largely disappear as we tighten our empirical design.[17]

Taken together, these layer-specific results reveal a hierarchical gradient that is masked in the pooled estimates. Within our most demanding job-mover specifications, managers who transition into remote jobs accept lower wages, whereas middle-layer professionals and lower-layer workers do not. Although time-varying sorting cannot be ruled out mechanically, the attenuation pattern from Columns 1 to 4 indicates that tightening comparability removes positive selection while preserving a robust negative managerial wage effect. This pattern is difficult to reconcile with a uniform compensating differential for remote work at the population level, but it is consistent with remote work being valued and priced differently across organizational layers.[18] In Section 7, we combine these wage responses with the firm-level evidence to interpret whether these observed wage changes can inform us about compensating differentials.

6. Remote Work Across Ranks and Firm Performance

Next, we discuss our firm-level results.

[17]Using employment spell start and end dates, we also re-estimate the event studies restricting the sample to worker-years in which the individual remains employed for the entire calendar year. This restriction drops approximately 10% of worker-year observations. Appendix Figures A1 and A2 repeat the analyses in Figure 3 and Figure 4 on this subsample. The negative managerial wage effect at $\tau = 1$ remains similar to the main-sample results.

[18]Consistent with this, survey evidence documents large heterogeneity in WFH valuation among European workers (Dias da Silva and Weissler, 2025).

6.1 Pooled Firm-Level Results

Table 2 reports pooled firm-level OLS estimates of the association between lagged firm-wide remote work adoption and firm performance (ROA). Across all three fixed effect specifications, the coefficient on WFH (all layers) is statistically insignificant. Hence, once firm fixed effects, rich controls, and time-varying dynamics across industries and locations are accounted for, the data do not indicate a strong relationship between overall remote work adoption and firm profitability. This pattern is in line with recent studies showing that aggregate effects can average out substantial heterogeneity across firms (e.g., Boeri, Crescenzi, and Rigo, 2025; Gupta, Gupta, and Simintzi, 2026).

6.2 Firm-Level Results By Layer

Table 3 reveals substantial heterogeneity masked by the pooled near-zero relationship between firm-wide remote work and ROA. Across all three specifications, the upper-layer and middle-layer coefficients are positive, while the lower-layer coefficients are negative. Taken together, these results suggest that remote work does not have a single uniform average association with firm performance; instead, its relationship with ROA differs systematically across organizational layers.

6.3 Remote Work Skew

The results so far suggest that the location of remote work implementation within the hierarchy is more consequential for firm performance than firm-wide adoption. To formally test this hypothesis, we relate ROA to both remote work adoption and its distribution within the firm, as per Equation (7).

Table 4 reports OLS estimates for Equation (7). Two results stand out. First, the coefficient on firm-wide remote work adoption is not statistically significant in any specification. Second, the coefficient on $WFHSkew_{j,t-1}$ is positive, statistically significant at the 1% level, and stable across fixed effect structures. Hence, holding constant remote work adoption, firms where remote work is more concentrated in the lower layer tend to display weaker subsequent performance.[19]

In Table 5, we estimate Equation (10) using the three layer-specific instruments introduced in Section 4. First-stage results in Table A6 show strong relevance: in the skew first stage, the upper-layer exposure instrument enters positively, and the lower-layer exposure instrument enters negatively,

[19]Tables A3, A4, and A5 repeat the analyses described so far in this Section in the unrestricted sample, with roughly similar results. This indicates that our OLS relationships are not driven by sample-composition differences between the unrestricted sample and the IV sample.

consistent with identification coming from differential layer-level shocks to remote work feasibility. Correspondingly, Sanderson-Windmeijer conditional first-stage F-statistics are large for both endogenous regressors, indicating no weak instrument concerns in these specifications. In addition, Sargan over-identification tests do not reject in any specification.

In the second stage, the IV estimates confirm the qualitative message of the OLS results. The skew coefficient remains positive and significant across all specifications. The coefficient on overall remote work adoption is also positive and becomes significant in two of the three specifications. This latter result is in line with Kwan, Matthies, and Yuskavage (2025), who show that the positive effects of remote work become more apparent in IV specifications. The skew coefficient is, however, the more stable of the two: it is positive and significant under both estimators, whereas the level coefficient is indistinguishable from zero under OLS and positive under IV.

Similar to Gupta, Gupta, and Simintzi (2026), we also document larger magnitudes of our IV estimates compared to the OLS. Two features of our setting explain why the IV estimates exceed their OLS counterparts (see also Jiang, 2017). On the one hand, this is consistent with measurement error in our remote work variable, which attenuates the OLS estimates closer to zero. On the other hand, the IV recovers a local average treatment effect: the instruments capture firms whose layer allocation of remote work shifted because their pre-pandemic occupational mix was differentially exposed to the 2019–2020 remote work shock. For these firms, adoption was abrupt and externally driven by occupational feasibility rather than being chosen optimally.

We also perform two sets of robustness tests for our IV results. First, as a placebo test, in Table A7 we regress the 2018-2019 change in ROA on the layer-specific instruments. We do not find any statistically significant coefficients, which is consistent with occupational compositions not reflecting differences in short-run firm performance before the pandemic. Second, we drop fiscal year 2020 to exclude the acute phase of the pandemic recession, when occupation-correlated demand shocks were most severe and therefore most likely to threaten the exclusion restriction.[20] Table A8 reports the results. The coefficient on WFH skew remains positive and statistically significant across all specifications, whereas the coefficient on overall WFH adoption is no longer statistically significant. This pattern is consistent with our earlier observation that skew is the more stable of the two endogenous regressors,

[20]Importantly, this test leaves the construction of the instruments untouched: the layer-specific exposure measures are still built from the 2019–2020 occupation-level remote work shock, and the sample is still restricted to firms with three layers in both 2019 and 2020. We are thus only trimming the years over which the second stage is estimated, not the variation that identifies the instruments.

and it reinforces our central firm-level conclusion: the allocation of remote work across the hierarchy is a more robustly identified determinant of firm performance.

We interpret the IV evidence as coherent and informative in suggesting an important role for remote work allocation across hierarchy, while acknowledging that our IV results are not definitive. Non-rejection in Sargan tests is reassuring, but such tests can have limited power and may fail to detect omitted channels that load similarly across all instruments. Likewise, the asymmetric level-versus-skew pattern is informative but cannot rule out every pandemic-era confounder that varies with occupational composition.

7. The Compensating Differential For WFH

The framework in Section 2 shows that identifying workers' valuation of WFH, δ_ℓ, requires combining the worker-side coefficient β^w_ℓ with the firm-side coefficient β^π_ℓ. We therefore interpret the evidence layer by layer, using the signs and magnitudes of the estimates presented in Sections 5 and 6.

For the upper layer, we estimate $\beta^w_U < 0$ (a wage decline of approximately 3% in our most restrictive job-mover specification) and $\beta^\pi_U \gtrsim 0$ (firm performance is weakly improved, or at least not worsened, when managerial WFH rises). In the notation of Equation (1), this pattern is consistent with $\mu_U \geq 0$. Under that sign restriction, Equation (2) applies directly and yields a conservative lower bound on the compensating differential for WFH of approximately 3%.

For the middle layer, both estimates are close to zero ($\beta^w_M \approx 0$ and $\beta^\pi_M \approx 0$). In this case, Equation (1) is weakly informative about δ_M: a small or zero amenity value is possible, but so are offsetting combinations of μ_M and rent-sharing. Accordingly, we do not claim point or bound identification for the middle layer.

For the lower layer, we find little evidence of a wage decline ($\beta^w_L \approx 0$), but significant evidence of negative firm-side consequences ($\beta^\pi_L < 0$). This sign combination does not satisfy the condition behind Equation (2), so the data do not support a lower-bound interpretation for δ_L. The evidence is instead consistent with $\mu_L < 0$ or wage rigidities that prevent wages from fully adjusting.[21]

Taken together, the interpretation is asymmetric across the hierarchy: the managerial layer is the

[21] Relative to countries like the United States, labor unions play a more important role in Finland, and therefore wage rigidity, especially for lower-level workers, is likely to be of interest. Moreover, Dias da Silva and Weissler (2025) find that 43% of fully remote employees would prefer fewer remote days, suggesting full-time remote work is often an employer-driven necessity rather than a chosen amenity.

only layer that identifies a conservative lower bound on the compensating differential for WFH, whereas the middle and lower layers remain only weakly informative about δ_ℓ. Our results help reconcile findings in the existing literature. Survey and experimental studies typically report willingness to pay for WFH in the 5–8% range (e.g., Mas and Pallais, 2017; Aksoy et al., 2022; Bartik, Cullen, Glaeser, Luca, and Stanton, 2025; De Fraja et al., 2025), whereas administrative studies find a positive remote work wage premium that is attributed to selection (Li, Sauvagnat, and Schmitz, 2026). Recent euro-area evidence from the ECB Consumer Expectations Survey sharpens this picture: 70 percent of employees would accept no pay cut at all for a hybrid arrangement, the average acceptable cut among workers whose jobs can be done remotely is 2.6 percent, and the average among the willing minority is 8.7 percent (Dias da Silva and Weissler, 2025). Our estimates mirror this distribution in revealed-preference terms: we document a near-zero differential for the broad workforce and a meaningful differential, with a conservative lower bound of approximately 3 percent, concentrated in a specific subgroup, managers.

8. Conclusion

This paper shows that the economic consequences of remote work depend not only on how much remote work a firm adopts but also on where remote work is located within the corporate hierarchy. In worker-level job-mover specifications, the unconditional wage premium associated with remote jobs masks substantial heterogeneity across layers. Managers who move into remote jobs experience wage declines of approximately 3% in our most demanding specifications, whereas middle- and lower-layer workers exhibit limited wage changes. At the firm level, aggregate remote work adoption is not strongly related to firm performance, but the allocation of remote work across layers is. Greater managerial remote work penetration is weakly associated with improved, or at least not deteriorated, performance, whereas greater lower-layer remote work penetration is associated with weaker firm performance.

These findings suggest that remote work is an organizational-design choice rather than a one-dimensional workplace amenity. For corporate finance, our results point to workplace flexibility as a component of organizational capital. This perspective helps reconcile worker-side evidence on compensating differentials with firm-side evidence on performance. In particular, when interpreted through our framework, the combination of managerial wage declines and non-negative firm-side performance effects supports a conservative lower-bound interpretation of the compensating differential for managerial remote work.

This paper also highlights the value of linking worker-side and firm-side moments within a common administrative-data environment. Our tax-based measure of high-intensity work from home, matched employer-employee records, occupational hierarchy measures, and firm financial statements allow us to study both the pricing of remote work in wages and its association with subsequent firm performance. At the same time, the evidence should be interpreted cautiously. Remote work is not randomly assigned, the Finnish institutional setting may affect external validity, and the compensating-differential result applies to managers under the maintained sign restriction implied by the firm-side evidence. Subject to these qualifications, our main conclusion is that the value of remote work for firms and workers is shaped by its allocation across the corporate hierarchy.

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Figure 1: Source of Information on Remote Work Uptake.
This screenshot shows how taxpayers can claim their home office deduction via the MyTax service, available on the website of the Finnish Tax Administration. Taxpayers in Finland can access and modify their tax reports free of charge either in person or online.

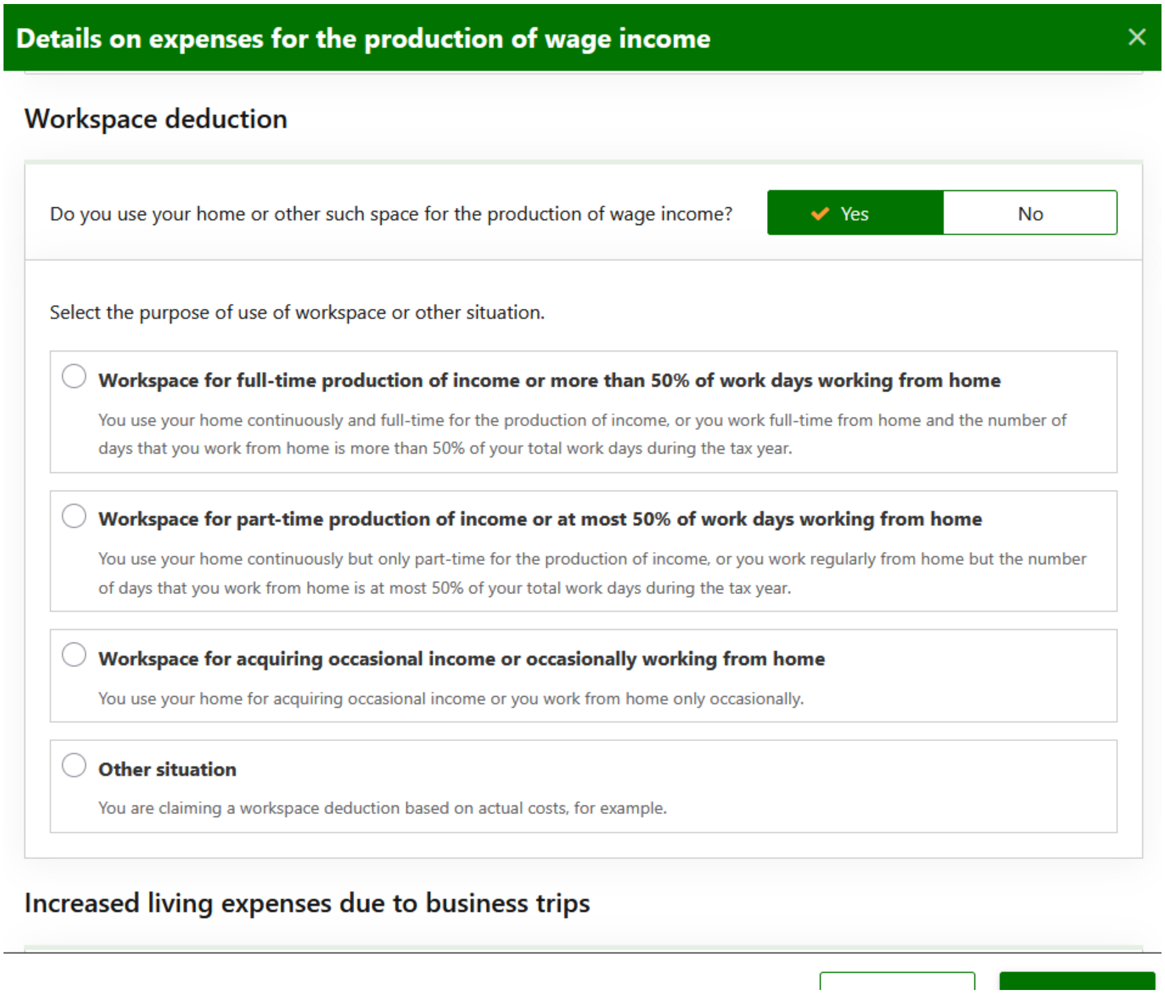


Figure 2: Remote Work Adoption by Occupational Layer Over Time.
This figure shows the yearly fraction of remote workers within a given layer. For each year, the measure is constructed by first computing firm-layer averages and then taking the mean of these firm-layer averages across firms.

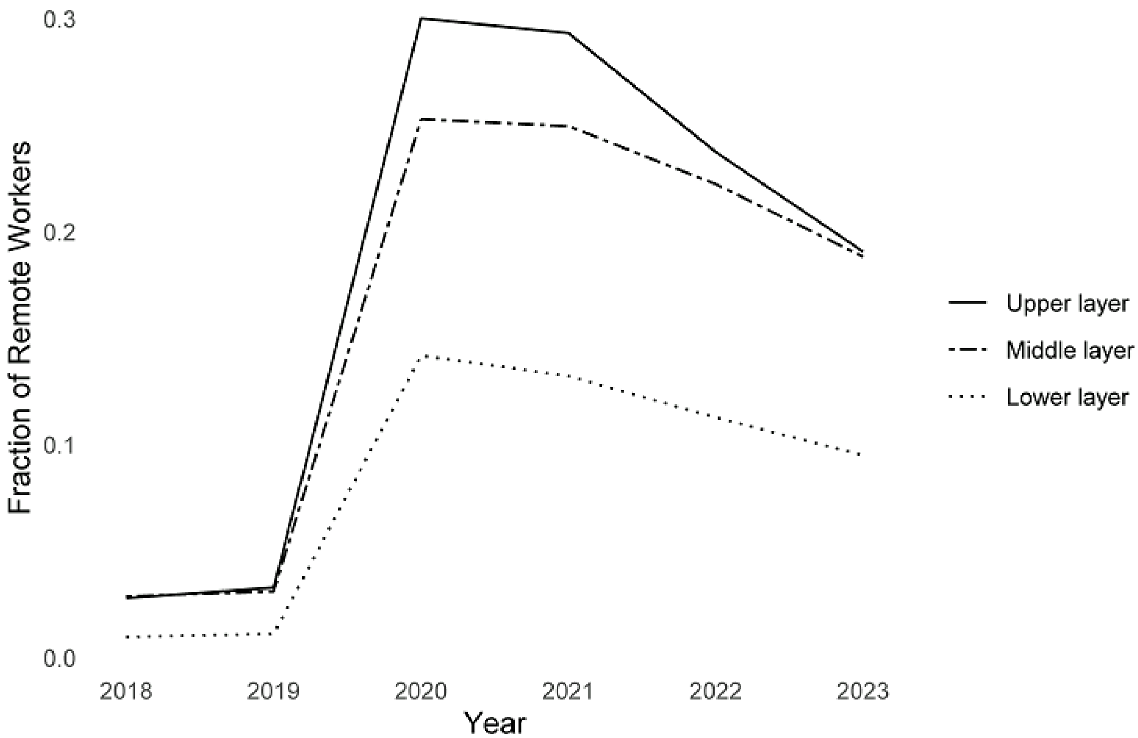


Figure 3: Wages When Moving Into Remote Jobs - All.
This figure shows β coefficients based on Equation (3). In the first figure, we do not exclude any job move. In the second figure, we exclude job moves where the 3-digit destination occupation does not match the origin occupation. In the third figure, we exclude jobs with *Teleworkability* < 0.3. In the fourth figure, we further include additional fixed effects. 95% confidence intervals are based on standard errors that are two-way clustered at the individual and origin-firm level. Regression results are reported in Table A1.

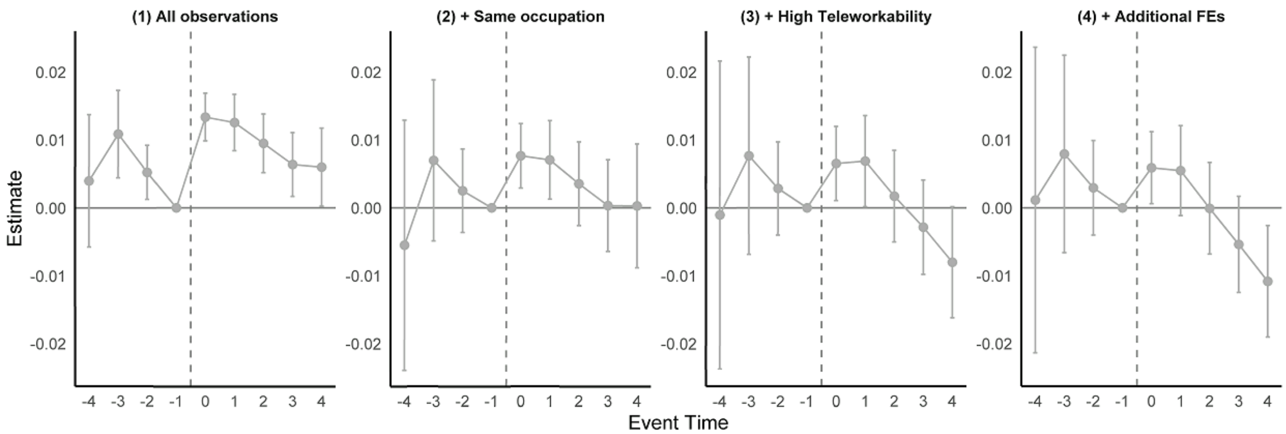
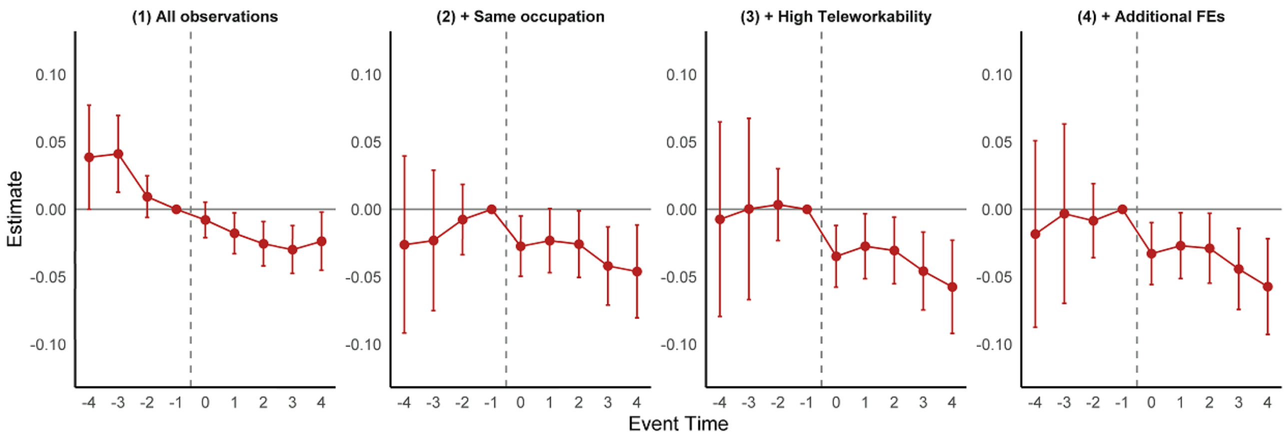
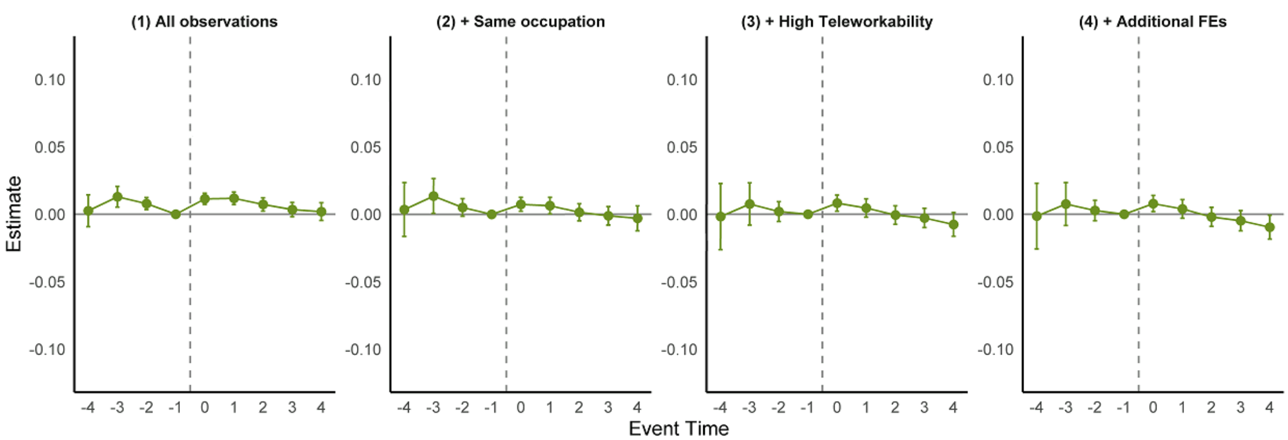


Figure 4: Wages When Moving Into Remote Jobs - By Layer.
This figure shows the dynamic wage effects of moving into a high-WFH job within each layer, based on Equation (4). In the first figure, we do not exclude any job move. In the second figure, we exclude job moves where the 3-digit destination occupation does not match the origin occupation. In the third figure, we exclude jobs with *Teleworkability* < 0.3. In the fourth figure, we further include additional fixed effects. 95% confidence intervals are based on standard errors that are two-way clustered at the individual and origin-firm level. Regression results are reported in Table A2.

Panel A: Upper Layer.



Panel B: Middle Layer.



Panel C: Lower Layer.

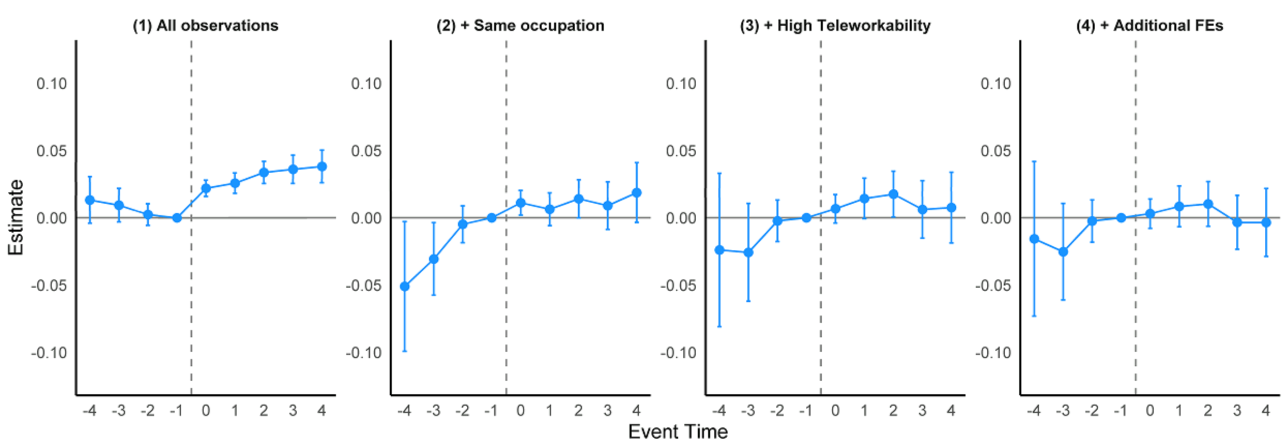


Table 1: Summary Statistics.
This table reports summary statistics. Panel A reports summary statistics at the worker-year level for our worker-level analyses. *Wage* is a register-based measure of individual wage and salary income. *WFH* is our measure of high-intensity telecommuting described in Section 3. The three worker-level layer classifications refer to the origin jobs. *Married* is an indicator variable equal to one if the individual is legally married or in a registered partnership, and zero otherwise. *University* equals one if the employee has completed a university degree, and zero otherwise. *Teleworkability* is a Finland-specific measure of teleworkability based on Dingel and Neiman (2020), measured at the 2-digit occupational code level. Panel B reports summary statistics at the firm-year level for the restricted IV sample. *WFH skew* is the difference between upper-layer WFH and lower-layer WFH. *ROA* equals net income scaled by total assets. *Leverage* equals total liabilities scaled by total assets. *Startup* is an indicator variable equal to one for firms in their first ten years of operation, and zero otherwise.

(a) Worker-Level Summary Statistics

Variable	N	Mean	SD	P25	P50	P75
Wage (€)	1,168,899	49,334	34,856	34,045	42,369	55,602
WFH	1,168,899	0.101	0.301	0.000	0.000	0.000
Upper layer	1,168,899	0.036	0.187	0.000	0.000	0.000
Middle layer	1,168,899	0.451	0.498	0.000	0.000	1.000
Lower layer	1,168,899	0.513	0.500	0.000	1.000	1.000
Age	1,168,899	42.22	10.84	33.00	42.00	51.00
Female	1,168,899	0.417	0.493	0.000	0.000	1.000
Married	1,168,899	0.465	0.499	0.000	0.000	1.000
University	1,168,899	0.408	0.491	0.000	0.000	1.000
Teleworkability	1,168,899	0.405	0.395	0.030	0.320	0.800

(b) Firm-Level Summary Statistics

Variable	N	Mean	SD	P25	P50	P75
No. of employees (all layers)	34,548	125.93	397.94	16.00	35.00	86.25
No. of employees (upper layer)	34,548	4.73	16.97	1.00	2.00	4.00
No. of employees (middle layer)	34,548	47.93	170.58	4.00	11.00	32.00
No. of employees (lower layer)	34,548	70.59	288.86	4.00	14.00	41.00
WFH (all layers)	34,548	0.124	0.190	0.000	0.029	0.167
WFH (upper layer)	34,548	0.180	0.311	0.000	0.000	0.300
WFH (middle layer)	34,548	0.161	0.229	0.000	0.023	0.267
WFH (lower layer)	34,548	0.083	0.202	0.000	0.000	0.030
WFH skew	34,548	0.096	0.297	0.000	0.000	0.111
ROA	34,548	0.034	0.512	-0.005	0.049	0.129
Leverage	34,548	0.609	0.472	0.373	0.575	0.768
ln(Assets)	34,548	15.70	1.62	14.54	15.64	16.88
Startup	34,548	0.190	0.392	0.000	0.000	0.000

Table 2: Remote Work and Firm Performance.
This table reports the results of OLS regressions based on Equation (5). The sample period is from 2019 to 2024. Only firms with three layers in both 2019 and 2020 are included. The unit of observation is a firm-year. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ROA		
	(1)	(2)	(3)
WFH (all layers)	0.0376	0.0408	0.0363
	(0.0282)	(0.0305)	(0.0273)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year $\times$ Industry (2-digit) FE	Yes	No	Yes
Year $\times$ Industry (4-digit) FE	No	Yes	No
Year $\times$ Region FE	No	No	Yes
N	34,510	34,102	33,596
Adjusted R^2	0.317	0.330	0.316

Table 3: Remote Work Across Ranks and Firm Performance.
This table reports the results of OLS regressions based on Equation (6). The sample period is from 2019 to 2024. The unit of observation is a firm-year. Only firms with three layers in both 2019 and 2020 are included. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ROA		
	(1)	(2)	(3)
WFH (upper layer)	0.0307***	0.0217*	0.0296***
	(0.0112)	(0.0115)	(0.0112)
WFH (middle layer)	0.0362*	0.0387*	0.0364*
	(0.0207)	(0.0211)	(0.0218)
WFH (lower layer)	-0.0572**	-0.0508*	-0.0588**
	(0.0290)	(0.0278)	(0.0290)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year × Industry (2-digit) FE	Yes	No	Yes
Year × Industry (4-digit) FE	No	Yes	No
Year × Region FE	No	No	Yes
N	34,510	34,102	33,596
Adjusted R^2	0.317	0.330	0.316

Table 4: Remote Work Skew.
This table reports the results of OLS regressions based on Equation (7). The sample period is from 2019 to 2024. The unit of observation is a firm-year. Only firms with three layers in both 2019 and 2020 are included. *WFH skew* is the difference between upper-layer WFH and lower-layer WFH. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ROA		
	(1)	(2)	(3)
WFH (all layers)	0.0286	0.0337	0.0273
	(0.0285)	(0.0306)	(0.0276)
WFH skew	0.0374***	0.0291***	0.0371***
	(0.0100)	(0.0101)	(0.0102)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year $\times$ Industry (2-digit) FE	Yes	No	Yes
Year $\times$ Industry (4-digit) FE	No	Yes	No
Year $\times$ Region FE	No	No	Yes
N	34,510	34,102	33,596
Adjusted R^2	0.317	0.330	0.316

Table 5: Remote Work Skew — IV.
This table reports the results of IV regressions based on Equation (10). The sample period is from 2019 to 2024. The unit of observation is a firm-year. Only firms with three layers in both 2019 and 2020 are included. *WFH skew* is the difference between upper-layer WFH and lower-layer WFH. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. The SW F-statistics are the Sanderson-Windmeijer conditional first-stage F-statistics for models with multiple endogenous variables (Sanderson and Windmeijer, 2016). Sargan's p-value refers to the test of overidentifying restrictions, with the null hypothesis that the overidentifying instruments are uncorrelated with the second-stage error term (Sargan, 1958). The first-stage regressions are reported in Table A6. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		ROA	
	(1)	(2)	(3)
WFH (all layers)	0.1924**	0.1406	0.2044**
	(0.0776)	(0.0901)	(0.0841)
WFH skew	0.2771**	0.1978*	0.2874**
	(0.1255)	(0.1195)	(0.1339)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year × Industry (2-digit) FE	Yes	No	Yes
Year × Industry (4-digit) FE	No	Yes	No
Year × Region FE	No	No	Yes
N	34,510	34,102	33,596
Adjusted R^2	0.317	0.330	0.316
SW F-statistic, *WFH (all layers)*	2,289	2,167	2,192
SW F-statistic, *WFH Skew*	632	612	608
Sargan's p-value	0.87	0.65	0.83

A. Appendix: Additional Results

Figure A1: Wages When Moving Into Remote Jobs - All (Robustness).
This figure repeats the analyses in Figure 3 restricting the sample to worker-years in which the individual remains employed for the entire calendar year. 95% confidence intervals are based on standard errors that are two-way clustered at the individual and origin-firm level.

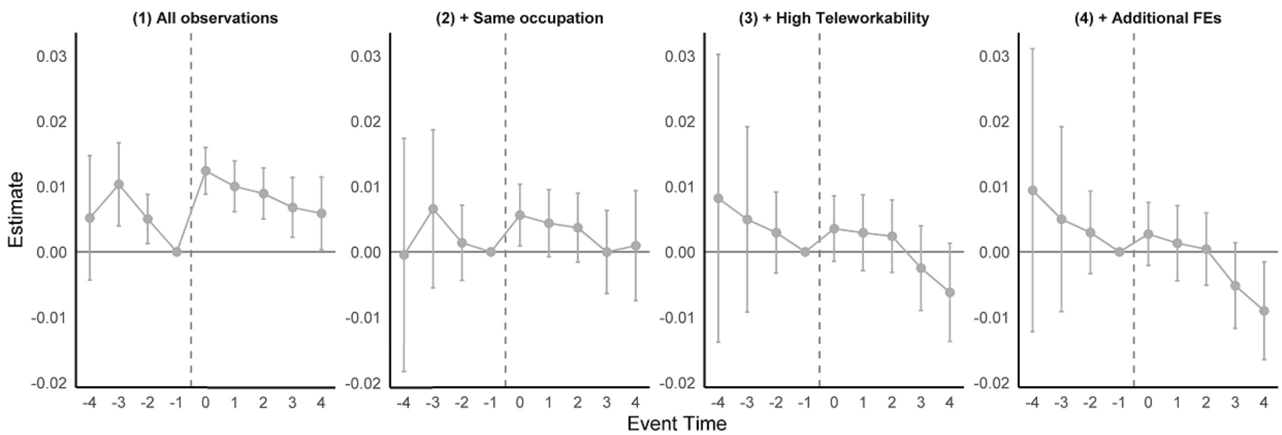
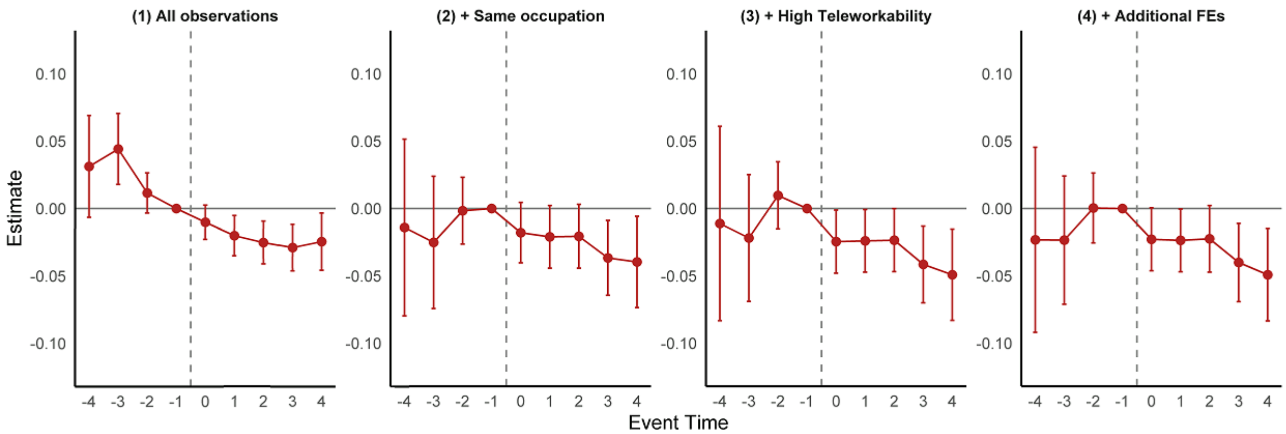
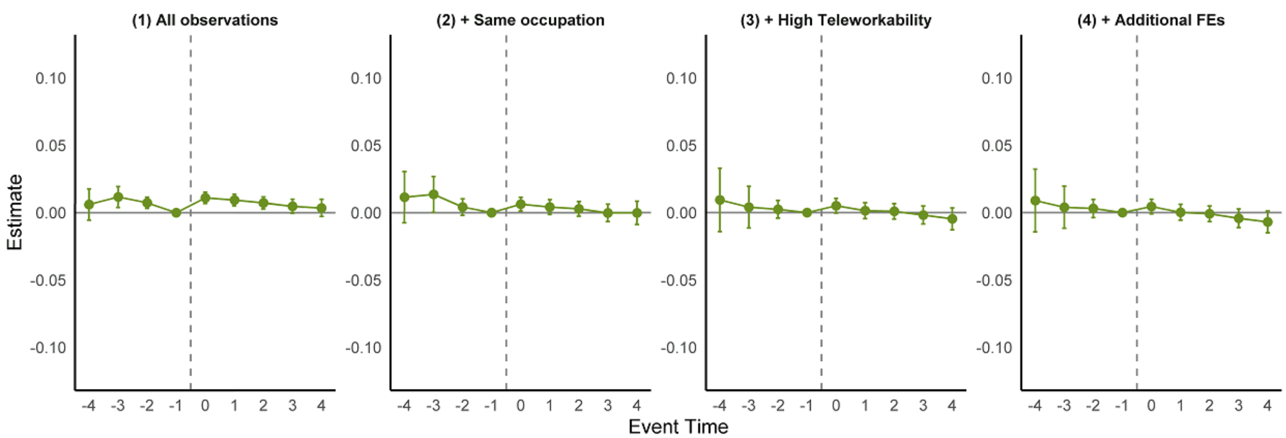


Figure A2: Wages When Moving Into Remote Jobs - By Layer (Robustness).
This figure repeats the analyses in Figure 4 restricting the sample to worker-years in which the individual remains employed for the entire calendar year. 95% confidence intervals are based on standard errors that are two-way clustered at the individual and origin-firm level.

Panel A: Upper Layer.



Panel B: Middle Layer.



Panel C: Lower Layer.

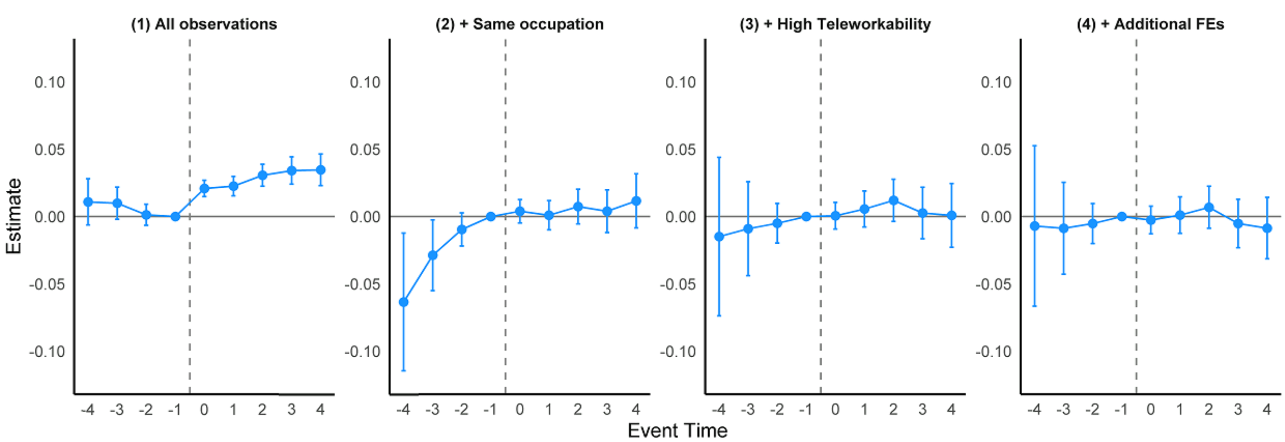


Table A1: Wages When Moving Into Remote Jobs — All.
This table reports the results of OLS regressions based on Equation (3). The sample period is from 2018 to 2023. The origin job is restricted to non-WFH. The unit of observation is a worker-year. Controls include *Age*, *Age squared*, *Married*, and *University*. In Column (1), we do not exclude any job move. In Column (2), we exclude job moves where the 3-digit destination occupation does not match the origin occupation. In Column (3), we exclude jobs with *Teleworkability* < 0.3. In Column (4), we further include additional fixed effects. Standard errors are two-way clustered at the individual and origin-firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ln(Wage)			
	(1)	(2)	(3)	(4)
GainWFH $\times \mathbb{1}(\tau = -4)$	0.0040	-0.0055	-0.0010	0.0011
	(0.0050)	(0.0094)	(0.0116)	(0.0115)
GainWFH $\times \mathbb{1}(\tau = -3)$	0.0109***	0.0070	0.0077	0.0079
	(0.0033)	(0.0060)	(0.0074)	(0.0074)
GainWFH $\times \mathbb{1}(\tau = -2)$	0.0052***	0.0025	0.0029	0.0030
	(0.0020)	(0.0031)	(0.0035)	(0.0036)
GainWFH $\times \mathbb{1}(\tau = 0)$	0.0134***	0.0077***	0.0065**	0.0059**
	(0.0018)	(0.0024)	(0.0028)	(0.0027)
GainWFH $\times \mathbb{1}(\tau = 1)$	0.0126***	0.0071**	0.0069**	0.0055
	(0.0021)	(0.0029)	(0.0034)	(0.0034)
GainWFH $\times \mathbb{1}(\tau = 2)$	0.0095***	0.0035	0.0017	-0.0001
	(0.0022)	(0.0031)	(0.0034)	(0.0034)
GainWFH $\times \mathbb{1}(\tau = 3)$	0.0064***	0.0003	-0.0028	-0.0054
	(0.0024)	(0.0034)	(0.0035)	(0.0036)
GainWFH $\times \mathbb{1}(\tau = 4)$	0.0060**	0.0003	-0.0080*	-0.0108***
	(0.0029)	(0.0046)	(0.0042)	(0.0042)
Controls	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes
Job-change cohort × year FE	Yes	Yes	Yes	Yes
Origin firm × year FE	Yes	Yes	Yes	Yes
Destination firm × year FE	Yes	Yes	Yes	Yes
Origin occupation × destination occupation FE	Yes	Yes	Yes	Yes
Occupation × year FE	No	No	No	Yes
Region × year FE	No	No	No	Yes
Sample	All	Same Occ.	Same Occ. + High TW	Same Occ. + High TW
N	991,406	489,392	220,986	220,986
Adjusted R^2	0.890	0.900	0.910	0.910

Table A2: Wages When Moving Into Remote Jobs — By Layer.
This table reports estimates of Equation (4). Panel A reports the baseline effect of gaining WFH for upper-layer workers (β_τ). Panel B reports layer-specific event-time effects common to WFH-gainers and non-gainers (β_τ^ℓ). Panel C reports differential effects of gaining WFH by layer ($\beta_\tau^{\ell W}$). The omitted period is $\tau = -1$, and the upper layer is the reference group. In Column (1), we do not exclude any job move. In Column (2), we exclude job moves where the 3-digit destination occupation does not match the origin occupation. In Column (3), we exclude jobs with *Teleworkability* < 0.3. In Column (4), we further include additional fixed effects. Standard errors are two-way clustered at the individual and origin-firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) Baseline Effect: Upper Layer

Dependent Variable:	ln(Wage)			
	(1)	(2)	(3)	(4)
GainWFH × $\mathbb{1}(\tau = -4)$	0.0385*	-0.0261	-0.0074	-0.0184
	(0.0197)	(0.0334)	(0.0368)	(0.0353)
GainWFH × $\mathbb{1}(\tau = -3)$	0.0410***	-0.0231	0.0002	-0.0033
	(0.0145)	(0.0266)	(0.0343)	(0.0339)
GainWFH × $\mathbb{1}(\tau = -2)$	0.0093	-0.0076	0.0034	-0.0085
	(0.0078)	(0.0133)	(0.0136)	(0.0140)
GainWFH × $\mathbb{1}(\tau = 0)$	-0.0079	-0.0273**	-0.0349***	-0.0329***
	(0.0067)	(0.0114)	(0.0117)	(0.0117)
GainWFH × $\mathbb{1}(\tau = 1)$	-0.0178**	-0.0232*	-0.0274**	-0.0271**
	(0.0077)	(0.0121)	(0.0123)	(0.0124)
GainWFH × $\mathbb{1}(\tau = 2)$	-0.0256***	-0.0259**	-0.0306**	-0.0289**
	(0.0084)	(0.0126)	(0.0126)	(0.0132)
GainWFH × $\mathbb{1}(\tau = 3)$	-0.0298***	-0.0420***	-0.0458***	-0.0443***
	(0.0090)	(0.0148)	(0.0147)	(0.0153)
GainWFH × $\mathbb{1}(\tau = 4)$	-0.0237**	-0.0461***	-0.0576***	-0.0574***
	(0.0110)	(0.0176)	(0.0176)	(0.0181)

(b) Layer-Specific Event-Time Effects

Dependent Variable:	ln(Wage)			
	(1)	(2)	(3)	(4)
Middle layer × $\mathbb{1}(\tau = -4)$	0.0310***	0.0335***	0.0528***	0.0194
	(0.0075)	(0.0129)	(0.0134)	(0.0155)
Middle layer × $\mathbb{1}(\tau = -3)$	0.0220***	0.0118	0.0169*	-0.0105
	(0.0053)	(0.0085)	(0.0091)	(0.0107)
Middle layer × $\mathbb{1}(\tau = -2)$	0.0060	0.0050	0.0140*	-0.0007
	(0.0040)	(0.0067)	(0.0073)	(0.0079)
Middle layer × $\mathbb{1}(\tau = 0)$	0.0197***	-0.0170**	-0.0230***	-0.0193***
	(0.0041)	(0.0067)	(0.0070)	(0.0072)
Middle layer × $\mathbb{1}(\tau = 1)$	0.0488***	-0.0136*	-0.0121	0.0072
	(0.0047)	(0.0073)	(0.0076)	(0.0095)
Middle layer × $\mathbb{1}(\tau = 2)$	0.0393***	-0.0133	-0.0084	0.0156
	(0.0052)	(0.0087)	(0.0090)	(0.0122)
Middle layer × $\mathbb{1}(\tau = 3)$	0.0405***	-0.0224**	-0.0228**	0.0059
	(0.0061)	(0.0101)	(0.0102)	(0.0157)
Middle layer × $\mathbb{1}(\tau = 4)$	0.0504***	-0.0208*	-0.0255**	0.0062
	(0.0075)	(0.0110)	(0.0116)	(0.0189)
Lower layer × $\mathbb{1}(\tau = -4)$	0.0505***	0.0543***	0.0394***	-0.0040
	(0.0077)	(0.0127)	(0.0143)	(0.0177)
Lower layer × $\mathbb{1}(\tau = -3)$	0.0384***	0.0215**	-0.0001	-0.0324**
	(0.0054)	(0.0087)	(0.0104)	(0.0127)
Lower layer × $\mathbb{1}(\tau = -2)$	0.0157***	0.0133**	0.0083	-0.0067
	(0.0040)	(0.0067)	(0.0076)	(0.0085)
Lower layer × $\mathbb{1}(\tau = 0)$	0.0100**	-0.0246***	-0.0259***	-0.0214***
	(0.0042)	(0.0065)	(0.0074)	(0.0078)
Lower layer × $\mathbb{1}(\tau = 1)$	0.0364***	-0.0268***	-0.0358***	-0.0159
	(0.0049)	(0.0073)	(0.0077)	(0.0106)
Lower layer × $\mathbb{1}(\tau = 2)$	0.0264***	-0.0310***	-0.0333***	-0.0109
	(0.0054)	(0.0087)	(0.0089)	(0.0138)
Lower layer × $\mathbb{1}(\tau = 3)$	0.0248***	-0.0431***	-0.0411***	-0.0151
	(0.0063)	(0.0101)	(0.0104)	(0.0184)
Lower layer × $\mathbb{1}(\tau = 4)$	0.0330***	-0.0458***	-0.0376***	-0.0094
	(0.0077)	(0.0113)	(0.0118)	(0.0218)

(c) Differential WFH Effects by Layer

Dependent Variable:	ln(Wage)			
	(1)	(2)	(3)	(4)
Middle layer × GainWFH × $\mathbb{1}(\tau = -4)$	-0.0360*	0.0296	0.0057	0.0170
	(0.0204)	(0.0347)	(0.0382)	(0.0368)
Middle layer × GainWFH × $\mathbb{1}(\tau = -3)$	-0.0281*	0.0366	0.0074	0.0108
	(0.0152)	(0.0275)	(0.0352)	(0.0349)
Middle layer × GainWFH × $\mathbb{1}(\tau = -2)$	-0.0015	0.0127	-0.0014	0.0112
	(0.0080)	(0.0137)	(0.0141)	(0.0146)
Middle layer × GainWFH × $\mathbb{1}(\tau = 0)$	0.0193***	0.0347***	0.0431***	0.0407***
	(0.0068)	(0.0115)	(0.0119)	(0.0121)
Middle layer × GainWFH × $\mathbb{1}(\tau = 1)$	0.0296***	0.0296**	0.0320***	0.0309**
	(0.0079)	(0.0122)	(0.0123)	(0.0126)
Middle layer × GainWFH × $\mathbb{1}(\tau = 2)$	0.0328***	0.0273**	0.0299**	0.0269**
	(0.0086)	(0.0128)	(0.0126)	(0.0134)
Middle layer × GainWFH × $\mathbb{1}(\tau = 3)$	0.0333***	0.0409***	0.0430***	0.0394**
	(0.0092)	(0.0148)	(0.0148)	(0.0154)
Middle layer × GainWFH × $\mathbb{1}(\tau = 4)$	0.0256**	0.0431**	0.0500***	0.0478***
	(0.0111)	(0.0178)	(0.0180)	(0.0185)
Lower layer × GainWFH × $\mathbb{1}(\tau = -4)$	-0.0253	-0.0250	-0.0166	0.0027
	(0.0211)	(0.0417)	(0.0468)	(0.0460)
Lower layer × GainWFH × $\mathbb{1}(\tau = -3)$	-0.0317**	-0.0076	-0.0260	-0.0219
	(0.0158)	(0.0300)	(0.0391)	(0.0388)
Lower layer × GainWFH × $\mathbb{1}(\tau = -2)$	-0.0069	0.0027	-0.0057	0.0060
	(0.0089)	(0.0150)	(0.0157)	(0.0162)
Lower layer × GainWFH × $\mathbb{1}(\tau = 0)$	0.0298***	0.0384***	0.0416***	0.0359***
	(0.0072)	(0.0121)	(0.0128)	(0.0130)
Lower layer × GainWFH × $\mathbb{1}(\tau = 1)$	0.0435***	0.0295**	0.0417***	0.0355**
	(0.0084)	(0.0134)	(0.0143)	(0.0146)
Lower layer × GainWFH × $\mathbb{1}(\tau = 2)$	0.0592***	0.0399***	0.0481***	0.0391**
	(0.0093)	(0.0143)	(0.0149)	(0.0156)
Lower layer × GainWFH × $\mathbb{1}(\tau = 3)$	0.0658***	0.0511***	0.0520***	0.0408**
	(0.0104)	(0.0169)	(0.0178)	(0.0182)
Lower layer × GainWFH × $\mathbb{1}(\tau = 4)$	0.0618***	0.0648***	0.0651***	0.0538**
	(0.0124)	(0.0200)	(0.0211)	(0.0211)

(d) Regression Details

Controls	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	Yes
Job-change cohort × year FE	Yes	Yes	Yes	Yes
Origin firm × year FE	Yes	Yes	Yes	Yes
Destination firm × year FE	Yes	Yes	Yes	Yes
Origin occupation × destination occupation FE	Yes	Yes	Yes	Yes
Occupation × year FE	No	No	No	Yes
Region × year FE	No	No	No	Yes
Sample	All	Same Occ.	Same Occ. + High TW	Same Occ. + High TW
N	978,436	489,197	220,889	220,889
Adjusted R^2	0.890	0.900	0.910	0.910

Table A3: Remote Work and Firm Performance — Full Sample.
This table reports the results of OLS regressions based on Equation (5). The sample period is from 2019 to 2024. The unit of observation is a firm-year. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		ROA	
	(1)	(2)	(3)
WFH (all layers)	0.0126	0.0060	0.0085
	(0.0263)	(0.0279)	(0.0262)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year × Industry (2-digit) FE	Yes	No	Yes
Year × Industry (4-digit) FE	No	Yes	No
Year × Region FE	No	No	Yes
N	49,621	49,257	48,032
Adjusted R^2	0.336	0.337	0.334

Table A4: Remote Work Across Ranks and Firm Performance — Full Sample.
This table reports the results of OLS regressions based on Equation (6). The sample period is from 2019 to 2024. The unit of observation is a firm-year. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ROA		
	(1)	(2)	(3)
WFH (upper layer)	0.0224**	0.0170*	0.0223**
	(0.0097)	(0.0097)	(0.0098)
WFH (middle layer)	0.0165	0.0104	0.0144
	(0.0180)	(0.0187)	(0.0188)
WFH (lower layer)	-0.0466**	-0.0441*	-0.0499**
	(0.0235)	(0.0237)	(0.0238)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year $\times$ Industry (2-digit) FE	Yes	No	Yes
Year $\times$ Industry (4-digit) FE	No	Yes	No
Year $\times$ Region FE	No	No	Yes
N	49,621	49,257	48,032
Adjusted R^2	0.336	0.337	0.334

Table A5: Remote Work Skew — Full Sample.
This table reports the results of OLS regressions based on Equation (7). The sample period is from 2019 to 2024. The unit of observation is a firm-year. *WFH skew* is the difference between upper-layer WFH and lower-layer WFH. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:		ROA	
	(1)	(2)	(3)
WFH (all layers)	0.0053	-0.0003	0.0010
	(0.0268)	(0.0285)	(0.0267)
WFH skew	0.0292***	0.0246***	0.0302***
	(0.0092)	(0.0094)	(0.0095)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year $\times$ Industry (2-digit) FE	Yes	No	Yes
Year $\times$ Industry (4-digit) FE	No	Yes	No
Year $\times$ Region FE	No	No	Yes
N	49,621	49,257	48,032
Adjusted R^2	0.336	0.337	0.334

Table A6: Remote Work Skew — First Stage.
This table reports the results of the first stage regressions for Table 5. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(a) WFH (all layers)

Dependent Variable:	WFH (all layers)		
	(1)	(2)	(3)
$Z^{upper}_{j,2019,2020} \times Post_{t-1}$	0.2399***	0.2098***	0.1952***
	(0.0223)	(0.0227)	(0.0223)
$Z^{middle}_{j,2019,2020} \times Post_{t-1}$	0.3772***	0.3518***	0.3564***
	(0.0203)	(0.0217)	(0.0202)
$Z^{lower}_{j,2019,2020} \times Post_{t-1}$	0.5866***	0.5323***	0.5512***
	(0.0329)	(0.0347)	(0.0318)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year $\times$ Industry (2-digit) FE	Yes	No	Yes
Year $\times$ Industry (4-digit) FE	No	Yes	No
Year $\times$ Region FE	No	No	Yes
N	34,510	34,102	33,596
Adjusted R^2	0.789	0.800	0.798

(b) WFH skew

Dependent Variable:	WFH skew		
	(1)	(2)	(3)
$Z^{upper}_{j,2019,2020} \times Post_{t-1}$	0.3717***	0.3563***	0.3568***
	(0.0446)	(0.0463)	(0.0461)
$Z^{middle}_{j,2019,2020} \times Post_{t-1}$	0.0609	0.0768*	0.0495
	(0.0395)	(0.0430)	(0.0402)
$Z^{lower}_{j,2019,2020} \times Post_{t-1}$	-0.3500***	-0.3293***	-0.3534***
	(0.0507)	(0.0539)	(0.0514)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year $\times$ Industry (2-digit) FE	Yes	No	Yes
Year $\times$ Industry (4-digit) FE	No	Yes	No
Year $\times$ Region FE	No	No	Yes
N	34,510	34,102	33,596
Adjusted R^2	0.346	0.340	0.344

Table A7: Placebo Test — Instruments and Pre-Pandemic Changes in Firm Performance.
This table reports placebo regressions of the 2018–2019 change in ROA on the layer-specific instruments used in the IV analysis. The unit of observation is a firm. The dependent variable is $\Delta ROA_{j,2018\to 2019} = ROA_{j,2019} - ROA_{j,2018}$. The regressors are the time-invariant layer-specific instruments $Z^{upper}_{j,2019,2020}$, $Z^{middle}_{j,2019,2020}$, and $Z^{lower}_{j,2019,2020}$, defined in Section 4. Controls are measured in 2018 and include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. Because the outcome is a single pre-pandemic change, the specification does not include firm or year fixed effects. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	$\Delta ROA_{2018\to 2019}$		
	(1)	(2)	(3)
$Z^{upper}_{j,2019,2020}$	-0.0034	-0.0027	-0.0079
	(0.0314)	(0.0330)	(0.0321)
$Z^{middle}_{j,2019,2020}$	0.0266	0.0202	0.0306
	(0.0302)	(0.0320)	(0.0311)
$Z^{lower}_{j,2019,2020}$	0.0305	0.0247	0.0315
	(0.0397)	(0.0429)	(0.0403)
Industry (2-digit) FE	Yes	No	Yes
Industry (4-digit) FE	No	Yes	No
Region FE	No	No	Yes
N	5,493	5,422	5,349
Adjusted R^2	0.023	0.032	0.021

Table A8: Remote Work Skew — IV (Excluding FY 2020).
This table reports the results of IV regressions based on Equation (10). The sample period is from 2019 to 2024 but excludes fiscal year 2020. The unit of observation is a firm-year. Only firms with three layers in both 2019 and 2020 are included. *WFH skew* is the difference between upper-layer WFH and lower-layer WFH. All regressors (including control variables) are lagged by one year. Controls include the natural logarithm of employees, ROA, a startup indicator, leverage, and the natural logarithm of assets. The SW F-statistics are the Sanderson-Windmeijer conditional first-stage F-statistics for models with multiple endogenous variables (Sanderson and Windmeijer, 2016). Sargan's p-value refers to the test of overidentifying restrictions, with the null hypothesis that the overidentifying instruments are uncorrelated with the second-stage error term (Sargan, 1958). The first-stage regressions are reported in Table A6. Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable:	ROA		
	(1)	(2)	(3)
WFH (all layers)	0.0689	0.0524	0.1029
	(0.0935)	(0.1014)	(0.1031)
WFH skew	0.3725**	0.3262**	0.3865**
	(0.1657)	(0.1512)	(0.1746)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year × Industry (2-digit) FE	Yes	No	Yes
Year × Industry (4-digit) FE	No	Yes	No
Year × Region FE	No	No	Yes
N	27,762	27,409	27,008
Adjusted R^2	0.281	0.297	0.280
SW F-statistic, *WFH (all layers)*	2,460	2,304	2,362
SW F-statistic, *WFH Skew*	408	395	395
Sargan's p-value	0.65	0.55	0.62

B. Appendix: Validation Tests of the Remote Work Measure

Our information on remote work uptake originates from tax reports and is therefore observed at the individual-year level. We operationalize our definition of remote work to identify self-reported high-intensity telecommuting (e.g., Gajendran and Harrison, 2007), as described in Section 3. Throughout the paper, we refer to such high-intensity telecommuting simply as “remote work.”

Below, we assess the validity of our remote work measure by examining its evolution over time, comparing it with survey-based evidence, and benchmarking it against other commonly used indicators of remote work.

B.1 Time Series

In Figure B1, we use our data to show how the number of employees who work from home evolves over time. Remote work among employees in Finland was a rather limited organizational phenomenon up to the COVID-19 pandemic. The uptake of remote work then spiked in 2020, when Finland implemented a number of policies to increase social distancing. Accordingly, major news outlets in Finland (including the national public broadcasting company) ran numerous stories, starting in Spring 2021, reminding readers of the existence of the home office deduction.[1] As the situation normalized over the following years, the number of individuals working from home in Finland gradually decreased. While remote work levels in Finland remain higher than in most other Western countries, the pattern described above is broadly consistent with the one observed across Europe (see, e.g., Jerbashian and Vilalta-Bufí, 2025).

B.2 Occupational Teleworkability

We validate our measure of remote work against the gold-standard measure of occupational teleworkability developed by Dingel and Neiman (2020). Importantly, the replication package of Dingel and Neiman (2020) allows us to build a Finland-specific measure of teleworkability for occupations identified at the major group (2-digit) level.[2] For example, occupations such as “information and communications technology professionals” have a teleworkability equal to one,

[1]See, for example, the following articles (in Finnish): `https://yle.fi/a/3-11726745`, `https://yle.fi/a/3-11882960`, and `https://www.mtvuutiset.fi/artikkeli/tarkeat-paivamaarat-lahestyvat-muista-nama-verovinkit-asiantuntija-vaantaa-myos-rautalangasta-tata-merkitsee-tyohuonevahennys-euroissa/8130980`.

[2]The replication package was retrieved from `https://github.com/jdingel/DingelNeiman-workathome` and compiled in March 2026.

whereas occupations such as "cleaners and helpers" have a teleworkability equal to zero. As shown in Figure B2, our data indicate that individuals in professions with higher teleworkability are substantially more likely to work from home (Pearson correlation of 0.89).[3]

B.3 Survey Evidence

Next, we compare our results with survey evidence. Statistics Finland administers two main surveys that measure conditions in the local labor market. The annual Labour Force Survey (*Työvoimatutkimus*, or LFS) has, since 2021, asked a remote work question to employed individuals aged 15–74, including the self-employed. In addition, the Quality of Work Life Survey (*Työolot*, or QWLS), which is conducted at intervals of around five years, recorded the share of remote work among wage income earners aged 18–67 for the reference year 2023.

We use the QWLS as our reference point because it allows us to map our remote work measure more closely to the survey answers. There are three main reasons for this choice. First, the remote work question in the QWLS refers to the entire previous calendar year, aligning with the tax return period we observe (whereas the LFS generally covers only the four weeks preceding the interview). Second, the QWLS provides more detailed frequency categories than the LFS, allowing us to better align our definition of threshold-based remote work. Third, the focus of this paper is on employees, whereas the prevalence of remote work is much higher among the self-employed (Aksoy et al., 2026).

Figure B3 reports the results of this comparison. Using tax reports, we find that 14.5% of full-time employees in Finland worked from home for more than 50% of all their working days in 2023. Our data map quite closely with the QWLS data for the same reference year. In fact, 16% of employees in the QWLS claimed to be working remotely for around 3/4 of the time or more, with an additional 6% declaring a share of remote work around 1/2 of the time. A bounds approach places the QWLS-implied prevalence between 16% and 22%, with a mid-point of 19%. Our tax-based estimate sits somewhat below this figure. This difference is consistent with three features of the institutional setting. First, employees who incur no out-of-pocket costs for remote work (e.g., because a parent or the employer pays for accommodation or work-related utilities) are not allowed to claim the deduction.[4] Second, the

[3] In Figure B2, we use 2020 data to match the real-time measures discussed in Dingel and Neiman (2020). Results are similar for other post-COVID years.

[4] For example, in 2024, about one-quarter of full-time employed young adults aged 18–34 in Finland lived with their parents. For more details, see `https://ec.europa.eu/eurostat/databrowser/view/ilc_lvps09/default/table?lang=en`.

QWLS is hours-based whereas our measure is days-based: depending on the taxpayers' interpretation of partial remote working days, the hours-based categories can substantially diverge from the days-based 50% threshold. Third, near-threshold claiming frictions (e.g., risk aversion, audit salience, and high tax morale) likely attenuate marginal claims relative to survey self-reports.

B.4 Industry

Next, we examine the shift to remote work across industries. Specifically, we compute the average change in our remote work measure across firms within each two-digit industry code from the pre- to the post-pandemic period, rank industries by this change from lowest to highest, and report the results in Table B1.[5] The resulting industry patterns are largely consistent with prior research (e.g., Dingel and Neiman, 2020). Labor-intensive industries experience the smallest increases in remote work, while knowledge-based industries experience the largest increases.

B.5 Commuting Distance

We also examine how the decision to work from home varies with commuting distance. Since a large literature in urban economics shows that commuting choices vary depending on urban spatial structure (e.g., Bento, Cropper, Mobarak, and Vinha, 2005; Redding and Turner, 2015), we examine how commuting distance affects the decision to work from home in the Finnish capital region, which consists of four municipalities and counts a population of about 1.3 million (with a median and average commuting distance of approximately 7 kilometers). Figure B4 confirms the basic stylized fact that shorter commuting distances are generally associated with a lower prevalence of remote work (Aksoy et al., 2022).

B.6 Gender

We further confirm the validity of our remote work measure by verifying the existence of a well-documented gender gap in remote work. Data from the US shows that women work from home slightly more than men (Barrero, Bloom, and Davis, 2023). The QWLS confirms the existence of a similar gap in Finland. We confirm this basic stylized fact using our measure of remote work. Figure

[5] We use two-digit industry codes. These industry codes are based on the Finnish TOL 2008 classification, which complies with NACE Rev. 2 on the 1 to 4-digit levels.

B5 plots the fraction of male and female employees working from home, showing the existence of a gender gap starting from 2020 onward.

B.7 Parenthood

Barrero, Bloom, and Davis (2023) find that the presence of children at home is strongly associated with increased working from home, with estimated effects ranging from 1.6 to 5.5 percentage points. Figure B6 confirms that this stylized fact also holds in our data.

Figure B1: Validation Tests of the Remote Work Measure - Time Series.
This figure plots the yearly count of full-time employees in our sample who work from home, between 2018 and 2023. The procedure to identify self-reported high-intensity telecommuting in a given year is described in Section 3.

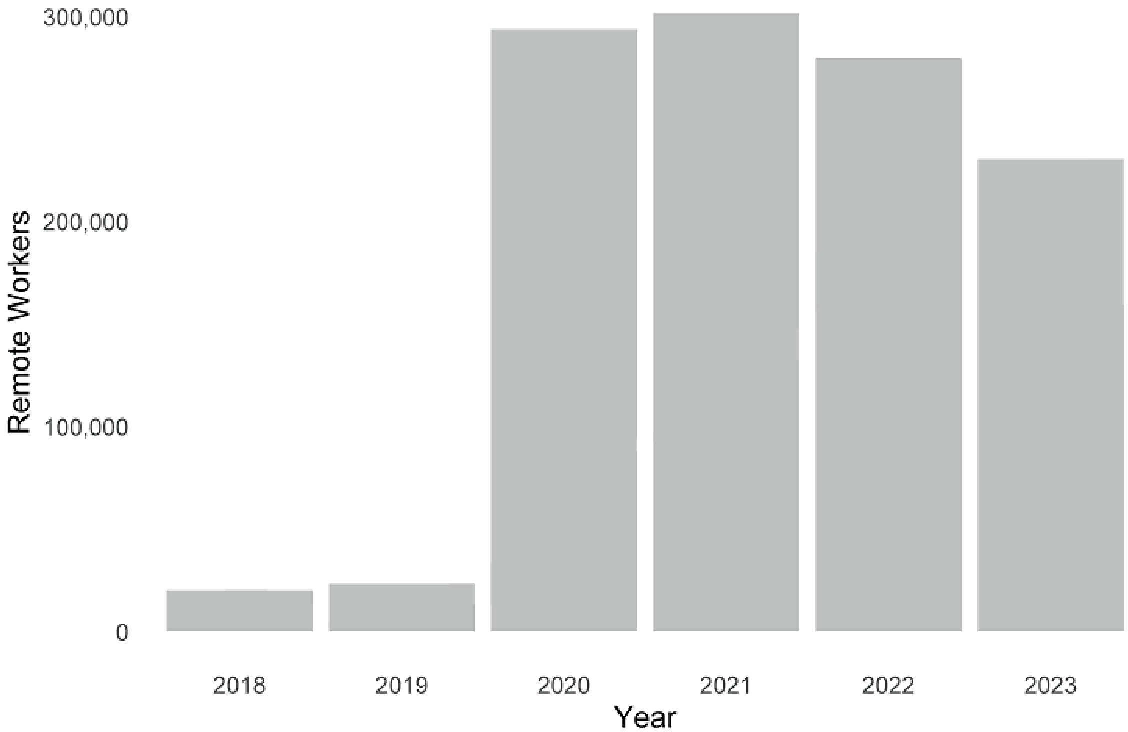


Figure B2: Validation Tests of the Remote Work Measure - Occupational Teleworkability.
This figure plots the frequency of remote work among employees in Finland in 2020 on the y-axis, and the Finland-specific teleworkability for 2-digit occupational codes derived from Dingel and Neiman (2020). Our data and the procedure to identify self-reported high-intensity telecommuting in a given year are described in Section 3.

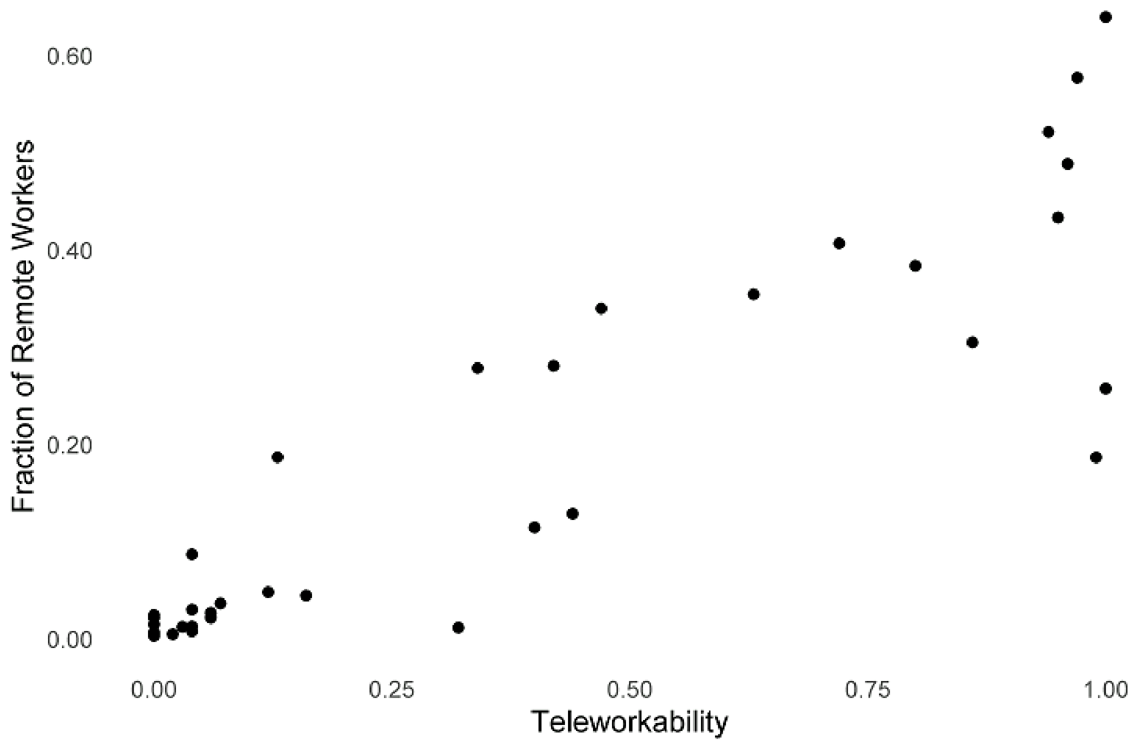


Figure B3: Validation Tests of the Remote Work Measure - Comparison With Survey Data.
This figure plots the frequency of remote work among employees in Finland in 2023. Our data and the procedure to identify self-reported high-intensity telecommuting in a given year are described in Section 3. The survey refers to the Quality of Work Life Survey administered by Statistics Finland and described in detail in Appendix B.3.

Figure B4: Validation Tests of the Remote Work Measure - Commuting Distance.
This figure shows the average propensity of remote work among full-time employees living and working in the Finnish capital region (Espoo, Helsinki, Kauniainen, and Vantaa) in 2020, as a function of their commuting distance. Each data point represents 10% of the observations. The procedure to identify self-reported high-intensity telecommuting in a given year is described in Section 3.

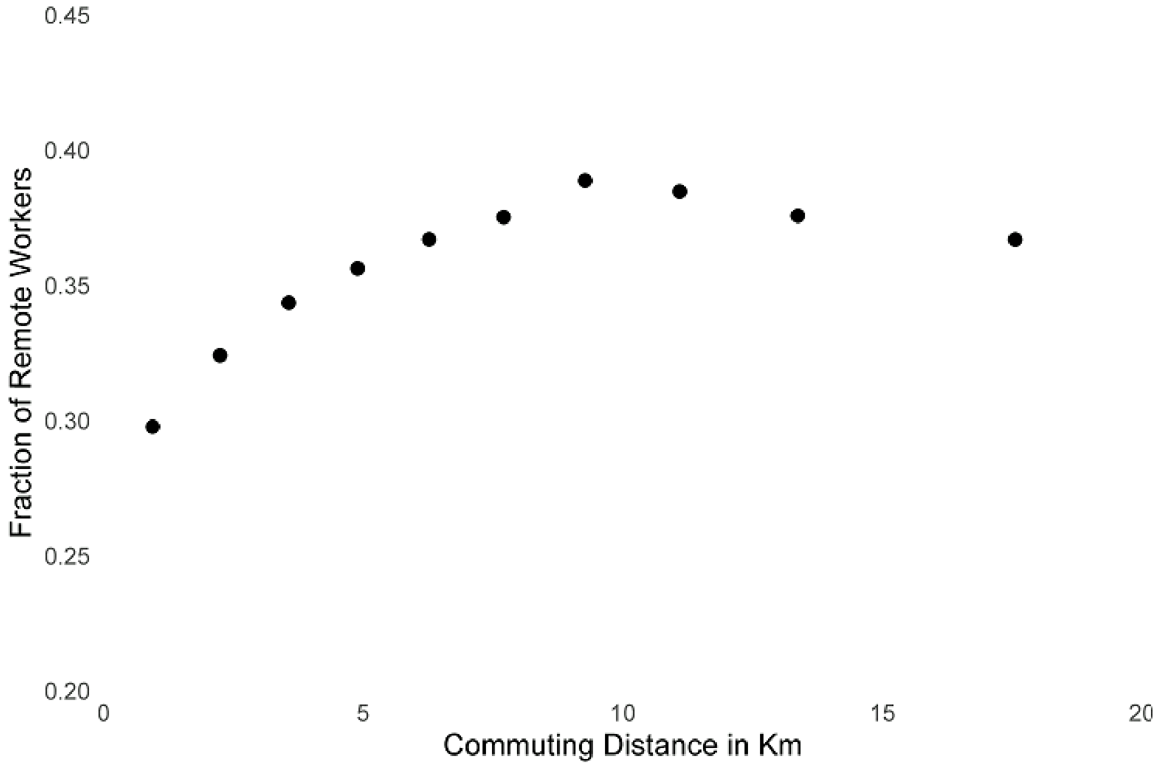


Figure B5: Validation Tests of the Remote Work Measure - Gender.
This figure shows the average propensity of remote work among full-time employees living in Finland between 2018 and 2023 by gender. The procedure to identify self-reported high-intensity telecommuting in a given year is described in Section 3.

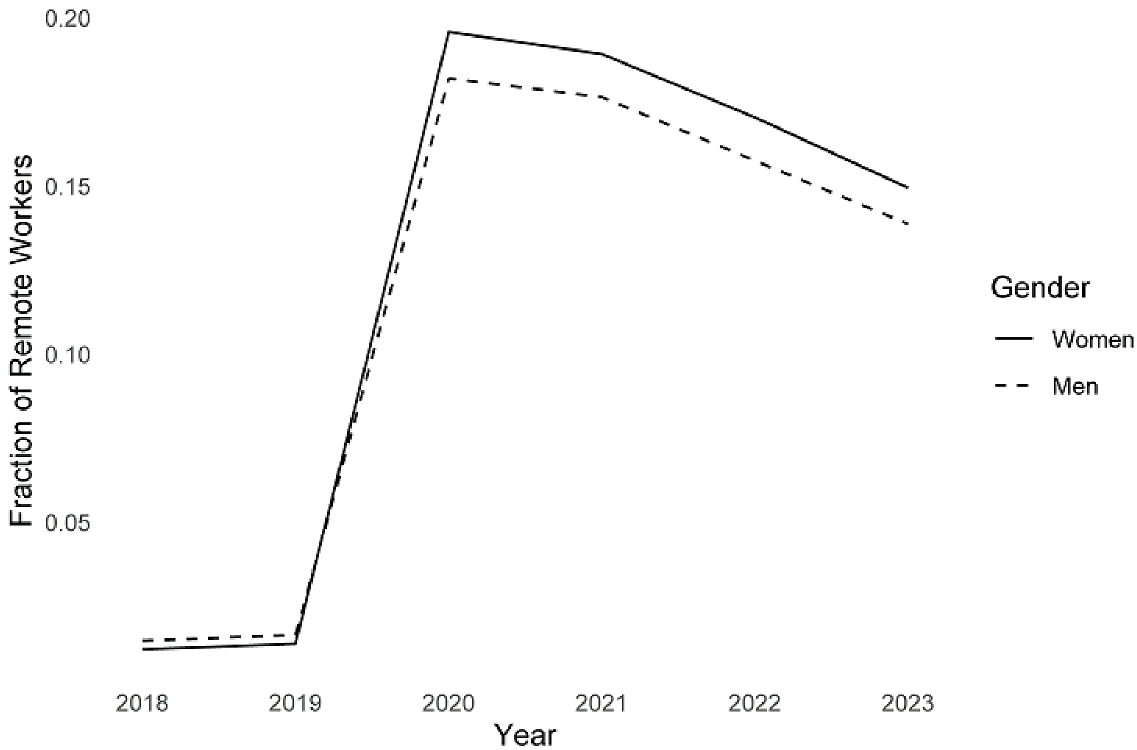


Figure B6: Validation Tests of the Remote Work Measure - Parenthood.
This figure shows the average propensity of remote work among full-time employees living in Finland between 2018 and 2023 by parenthood status (i.e., having underage children in a given calendar year). The procedure to identify self-reported high-intensity telecommuting in a given year is described in Section 3.

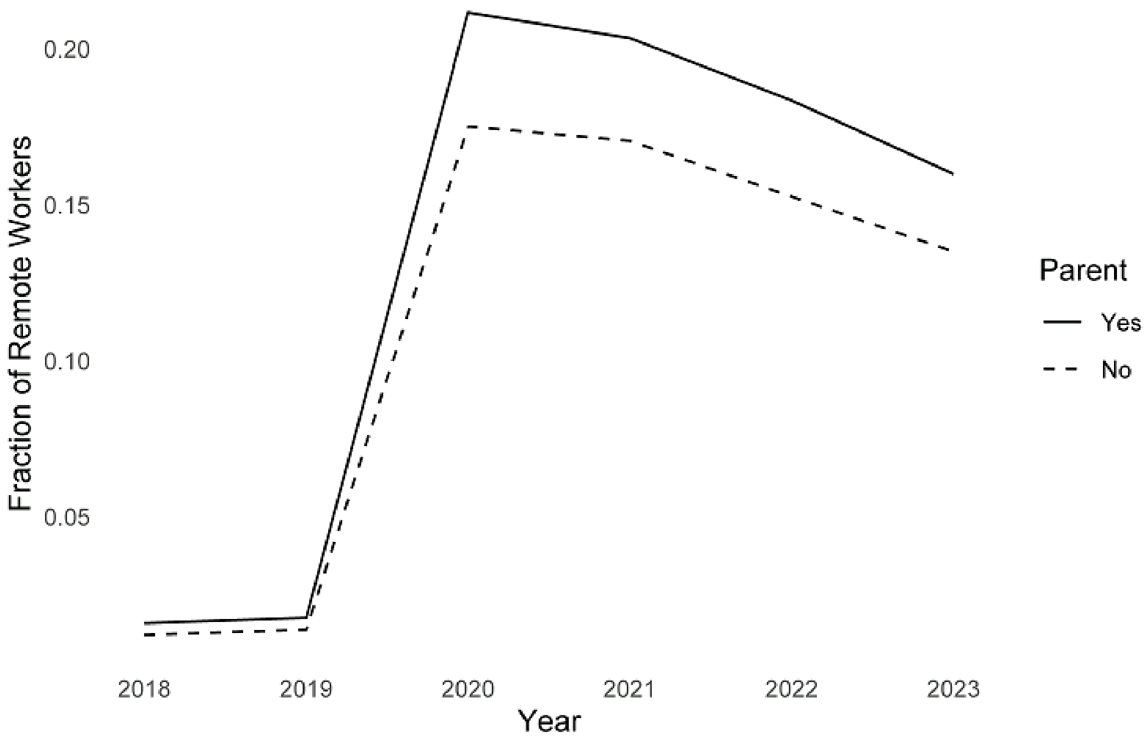


Table B1: Validation Tests of the Remote Work Measure - By Industry.
This table lists industries (two-digit TOL 2008 codes) with the largest and smallest shifts toward remote work from 2018 to 2023. Industries are ordered by the magnitude of the shift, in descending order. Industries with fewer than 1 000 workers in either year are omitted.

(a) Industries with Largest Shifts

Code	Industry
61	Telecommunications
66	Activities auxiliary to financial services and insurance activities
62	Computer programming, consultancy and related activities
63	Information service activities
65	Insurance, reinsurance and pension funding, except compulsory social security

(b) Industries with Smallest Shifts

Code	Industry
81	Services to buildings and landscape activities
49	Land transport and transport via pipelines
56	Food and beverage service activities
87	Residential care activities
15	Manufacture of leather and related products