Here, There, and Everywhere: Remote Work's Impact on Employment for Older and Disabled Workers in the UK [1]

By

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Abstract: Remote work is frequently touted as a way for disabled and older workers to remain in the labour market. Post-Covid, the incidence of remote work has increased in the UK, providing a potential natural experiment to test the causal effects. We first replicate Bloom et al. (2026)'s findings on the positive effects of remote work on employment for US disabled workers in our UK setting, despite the highly different institutional context. We then extend this analysis to show similar positive employment results for older workers in the UK, using the pandemic's increase in work from home rates as a quasi-experiment. The methodology compares occupations with high growth in work from home (WFH) to those with lower growth in work from home, with growth rates measured among the non-disabled or younger, then instrument using pre-pandemic remote work scores from De Fraja et al. (2021). Finally, we explore mechanisms by considering impacts on other labour market outcomes, finding decreases in commute time and wages for both groups, but no effect on hours worked.

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Introduction

Disabled and older people have substantially lower employment rates in the UK. Fifty-seven percent of the UK working age population who reported a work-limiting health condition in 2024 are not working (Mayfield, 2025a). While not as stark a contrast, more than a quarter of those between the ages of 50 and 64 were not working (Jendrzejewski and Briedis, 2025). UK policymakers argue that remote work is a low-cost adjustment employers can make to promote labour force attachment among disabled or older workers (e.g., Mayfield, 2025b). They also argue that remote work has the potential to create pathways to a more inclusive labour market by removing physical and commuting barriers to work, enabling workers to manage health conditions more easily, and offering flexibility around caring responsibilities (Mayfield 2025b). According to a recent employer survey commissioned by the House of Lords Select Committee on Home-Based Working (2026), 28% of employees with health conditions worked from home as an adjustment, and 19% wished they could work from home more. Yet it is unclear whether greater access to remote work brings people into employment or changes where existing workers perform their jobs.

Previous work in the US suggests that rising rates of remote working may lead to increased employment opportunities for disabled workers and older workers. Rising remote-work availability is associated with higher employment rates among disabled workers in occupations with greater remote potential (Ne'eman & Maestas, 2023; Bloom et al., 2026; Tseng & Webber, 2025). The strong correlation between age and disability suggests remote-work gains for disabled workers may also benefit older workers (Liu & Quinby, 2024; Bloom et al., 2026). Remote work is also shown to reduce the desire to retire among older workers (Sanzenbacher, 2025). However, in the UK, occupational sorting may constrain the benefits of remote work because disabled workers are disproportionately represented in roles with lower remote-work feasibility (Schur et al., 2021; Ameri et al., 2023) and remote work is most common among older workers in the UK who are already unlikely to exit the labour force (Coombs et al., 2021). UK datasets also capture a more comprehensive definition of disability compared to the US because of differences in survey questions, which means the marginal disabled worker may differ across the two countries for purely definitional reasons (Department for Work and Pensions (DWP), 2025).

In this paper, we empirically test the relationship between rising work from home (WFH) rates and employment outcomes for disabled and older workers in the UK. We examine the effect of remote working on two groups: workers with a physical disability, who often face mobility, transport, and workplace-access barriers, and older workers, who are likely to exit the labour market prior to pension age due to health or caring responsibilities. Using the pandemic-induced expansion in remote work as a quasi-experiment, we compare changes in employment across occupations that experienced larger

versus smaller increases in WFH during the pandemic. To reduce concerns of reverse causality, we use the expansion of WFH among non-disabled or younger workers as a proxy for the growth in WFH among disabled or older workers. To isolate plausibly exogenous variation in occupation-level WFH growth, we instrument changes in WFH with pre-pandemic measures of occupations' ability to be performed remotely (Dingel and Neiman, 2020; De Fraja et al., 2021).

Using our main Instrumental Variable (IV) results, we find that a 1 percentage point increase in change in WFH from pre- to post- Covid, as instrumented by the WFH index, increases full-time employment in an occupation by 0.9% for disabled people with a physical disability in the UK. This increase is remarkably close to the increase found in the US, despite the myriad institutional differences between the two countries. Using a similar specification but focusing on older adults, we find a consistent increase of about half the size of the disability effect, at 0.38%, suggesting that WFH also bolsters the full-time employment of older people in the UK. Our results are robust to including all types of employment, definitions of disabilities, different age groups, and separating by gender. We also use the same IV strategy to look at other outcomes and find that WFH decreases wages and commute times.

We see our contributions to the literature as three-fold. First, the previous literature is primarily US-focused, and the US is unique in many aspects (Ameri et al. 2023; Bloom et al. 2026; Ne'eman & Maestas, 2023; Tseng & Webber 2025). Second, we are using causal techniques to build on non-causal UK estimates on the disabled from early in the pandemic (Hoque and Bacon, 2022; Jones, 2022), and non-causal US and UK estimates for older workers (e.g. Sanzenbacher, 2025; Coombs et al., 2021). Third, we examine both disabled workers and older workers using the same framework so that effects of WFH on the two groups can be directly compared. These are groups that face similar barriers in the labour market and for whom work from home could be a policy lever that induces higher attachment to the labour force.

Previous Literature and UK Institutional details

Rising remote-work availability is associated with higher employment rates among disabled workers in US occupations with greater remote potential (Ne'eman & Maestas, 2023; Bloom et al., 2026; Tseng & Webber, 2025). Ne'eman and Maestas (2023) provide evidence that the post-pandemic rise in remote work is linked to increases in employment among disabled workers, particularly in occupations with high "remote potential." They argue this is driven by constraint relaxation: many disabled individuals face barriers tied to commuting, workplace accessibility, fatigue, or the need for flexible scheduling, and remote work directly reduces these frictions. Recent work by Tseng and Webber (2025) finds that gains in employment of disabled people are concentrated in occupations with higher telework prevalence. Hoque and Bacon (2022) examined whether working from home (WFH) is correlated with improved employment outcomes for disabled people in the UK using similar non-causal methods. Using

nationally representative data, the authors show that disabled employees are actually less likely to have access to homeworking than non-disabled workers, largely because they are underrepresented in higher-paid and managerial roles where such flexibility is most available. Even when WFH is available, it does not appear to significantly reduce labour market inequalities, but it is associated with better job satisfaction, mental health, and job control for all workers. Similarly, Rodgers et al. (2026) find that among US healthcare workers, remote work improves most perceptions of work experiences for workers with and without disabilities, but does so more for the latter, so it does not narrow disability gaps in these experiences. The authors argue that structural barriers, such as occupational segregation of disabled workers, may limit the role of WFH in reducing the disability employment gap in the UK.

We might also expect an effect of WFH on employment for older workers, first, because there is a strong correlation between age and disability, suggesting that remote-work gains for disabled workers may also benefit older workers (Liu & Quinby, 2024), and additionally, because, as a recent Current Population Survey (CPS) questionnaire suggests, remote work reduces the desire to retire among older workers (Sanzenbacher, 2025). On the other hand, remote work among older workers is already highest among those least likely to leave the labour force (Coombs et al., 2021), suggesting WFH could have a limited effect for older workers.

The work most similar to ours is Bloom et al. (2026) who find that increases in remote work potential lead to increases in disability employment in the US context. Specifically, they find that a 1 percentage point increase in WFH raises full-time employment of people with a physical disability by 1%, explaining about 70 to 85% of the rise in full-time employment among this group during the post-pandemic period. To distinguish labour supply from demand effects, they compare wage growth in high- versus low-WFH occupations before and after the pandemic.

We follow their IV strategy to explore the analogous relationship in the United Kingdom. There are several reasons to believe that the response to increased work from home may be muted in the United Kingdom compared to the United States. First, in the UK more than in the US, disabled workers are disproportionately represented in occupations with lower remote-work feasibility, such as retail (Schur et al., 2021; Ameri et al., 2023), suggesting that, all else equal, increases in remote-work occupations may have less of an effect on disabled workers as a whole. Second, disability is measured more comprehensively in UK surveys than in US surveys, suggesting that the marginal disabled person may be less severely disabled in the UK than in the US (although there are scenarios in which the sign of the effect could go the other direction) (DWP, 2025).. Pushing in the opposite direction, Hansen et al. (2023) find that listings for remote work in the UK rose at 5x the rate of listings for remote work in the US, suggesting a larger capacity for growth in WFH occupations in the UK compared to the US.

Finally, the UK had generous furlough programmes during the pandemic, which supported firms to pay the wages of workers who could not work due to lockdown restrictions. Disabled workers were disproportionately placed on furlough or temporarily away from work during the pandemic (Jones, 2022). Jones (2022) argues that because aggregate employment effects of the pandemic appear muted for disabled workers, furlough may have acted as a buffer, preventing sharper employment losses among disabled workers that might otherwise have occurred.

Theory

We consider the effects of working from home (WFH) within a standard labour search model where employment and wages are shaped by frictions that prevent workers and firms from matching costlessly and by heterogeneity in firms' willingness to hire particular groups. Workers receive job offers at some arrival rate and decide whether to accept them based on whether the offered wage exceeds their reservation wage. Firms may possess monopsony power because workers face geographic, informational, and mobility constraints that limit the number of employers from which they can realistically receive and accept offers. These constraints weaken workers' outside options and allow firms to offer wages below the level that would prevail in a frictionless market. Following Black (1995), discrimination can further intensify this monopsony power. When some firms are unwilling to hire disabled or older workers, the effective set of employers available to those workers contracts, reducing both their job-offer arrival rate and their bargaining position. Working from home may alter these outcomes by expanding the effective set of jobs and employers available to workers, reducing the costs associated with accepting and retaining employment, and changing firms' costs of hiring and accommodating particular workers.

On the labour-supply side, working from home can increase employment by lowering the monetary and non-monetary costs of accepting and retaining a job. Commuting may be especially costly for workers with mobility limitations, chronic pain, fatigue, or other health conditions, as well as for older workers with health constraints or caring responsibilities. These costs include not only travel expenses and commuting time, but also the physical effort, scheduling difficulties, and uncertainty associated with reaching and navigating a workplace. WFH reduces or eliminates many of these costs, thereby increasing the net value of employment relative to unemployment or labour-force non-participation. In a search framework, this reduction in work-related costs lowers the wage a worker must be offered for a job to be worthwhile and increases the proportion of offers the worker is willing and able to accept. Consequently, greater access to WFH should increase job-acceptance rates, shorten periods of non-employment, and make it easier for workers whose constraints would otherwise prevent employment to enter or remain in the labour market.

A second channel operates through the range and suitability of available jobs. When regular attendance at a fixed workplace is no longer required, workers can search over a wider geographic area and receive offers from employers located beyond a feasible commuting distance. This expansion is particularly valuable for disabled and older workers, whose local employment options may be limited by inaccessible transport, unsuitable workplaces, or the need to remain close to home. Remote arrangements may also provide greater control over the physical work environment and, in some cases, the timing of work, allowing workers to manage fatigue, medication, medical appointments, assistive technologies, or caring responsibilities more effectively. These features increase the value and expected duration of suitable matches and may reduce exits from employment. For disabled workers, these mechanisms may increase entry into or retention in full-time employment. For older workers, they may also delay retirement or shift employment toward occupations in which remote work expanded.

On the labour-demand side, remote work changes the set of workers firms can recruit. Removing the requirement to live within commuting distance allows firms to draw from a broader geographic market, increasing the likelihood of finding workers whose skills and constraints are well matched to the job. Remote recruitment and work may also reduce the salience of some visible impairments and lessen employers' concerns about workplace accessibility, attendance, and accommodation costs. When work can be performed from home, some workplace-specific accommodations may be reduced or avoided because workers can use an environment already adapted to their needs. Remote work may similarly help firms retain older workers whose health constraints or caring responsibilities make regular workplace attendance difficult. In a search framework, these lower expected employment costs increase the surplus generated by a match and may raise firms' willingness to recruit, hire, and retain disabled and older workers. Following equilibrium search models with discriminatory firms, reducing these barriers may also expand the set of firms willing to employ these workers and weaken the monopsony power of the firms that already do so. On balance, these demand-side mechanisms predict greater hiring and retention in occupations where WFH opportunities expand. Thus both supply and demand considerations suggest that increased WFH will lead to increased employment for disabled and older workers.

The predicted effect of WFH on wages is ambiguous because several mechanisms operate in opposing directions. Lower commuting and workplace costs may reduce workers' reservation wages, while competition for remote vacancies may increase as firms recruit nationally rather than locally. Both forces would place downward pressure on wages. Working in the opposite direction, access to a wider set of employers may improve workers' outside options, while better matches, higher productivity, and lower accommodation costs may increase the surplus available to be shared between firms and workers. Whether wages rise or fall therefore depends on which set of mechanisms dominates.

The effects of WFH on hours worked is also theoretically ambiguous. Hours may increase if remote work allows individuals who would otherwise work part time, take extended absences, or leave employment to sustain longer or full-time schedules. Greater control over the work environment may help disabled and older workers manage health conditions, fatigue, medical appointments, and caring responsibilities without reducing their labour supply. However, remote work may instead allow some workers to remain employed while working fewer hours, and firms may offer remote positions with shorter or more variable schedules.

Data and Descriptive Statistics

We use data from the Quarterly Labour Force Survey (QLFS) from the United Kingdom (ONS 2025). The QLFS is a nationally representative rotating household survey in which respondents are interviewed for five consecutive quarters conducted by the Office for National Statistics (ONS), providing data on the labour market, including economic activity and job characteristics. Each quarter, 20% of the sample is replaced by new households. The sample includes people aged 16 and over, covering the UK population except for communal establishments like hospitals, prisons, and military barracks. We restrict the sample to individuals aged 18 to 64 in the UK in the QLFS between quarter 1, 2018 and quarter 4, 2024. For the majority of our analyses, we limit the sample to years 2018-2019 and 2023-2024.

We classify a respondent as physically disabled if they meet the Equality Act 2010 disability definition (GSS Harmonisation 2019) and report physical, but no cognitive, health conditions. Respondents who do not meet the Equality Act definition form the non-disabled comparison group. Respondents who meet the Equality Act definition but report any cognitive conditions are excluded from the baseline disability analysis, although they are included in robustness checks and remain in the age-based sample. Respondents are asked, “Do you have any physical or mental health condition or illness lasting or expected to last 12 months or more?” If they answer “No”, the person is not classified as disabled. If they answer “Yes”, they are then asked, "Does your condition or illness reduce your ability to carry out day-to-day activities?" If they answer “Yes, a lot” or “Yes, a little” they are classified as disabled under the Equality Act 2010 definition. If they answer “not at all”, they are not classified as disabled. If the respondent reports an impact on daily activities, they are asked to specify the nature of their condition, such as mobility issues, mental health conditions, sensory impairments (vision or hearing), chronic illnesses, or learning difficulties. In our baseline specifications, we follow Bloom et al. (2026) and focus on individuals with a physical disability, since autism and ADHD were not measured pre-Covid in the QLFS.[2]

[2] Approximately 20% of the population had a disability of any type pre-Covid and 24% had a disability of any type post-Covid. We further classify these conditions into physical or cognitive disabilities. Prior to COVID, 72% of disabled individuals listed their primary health problem as physical in nature and 27% listing a health problem that is cognitive. As a

We first examine changes in full-time employment to assess whether post-pandemic labour market recovery differed across disability status and age groups. Figure 1 presents the evolution of the share of individuals employed full-time, as the percent change relative to 2019Q1. Figures 1a and 1c report the results for disabled vs. non-disabled individuals. Full-time employment was more common among non-disabled individuals (65.0%) than among disabled individuals (37.7%) the year before COVID. The rate rose for both disabled and non-disabled individuals post-Covid, with a slightly larger increase among disabled individuals. Figures 1b and 1d report the results for younger vs. older individuals. Full-time employment was also more common among individuals aged 18 to 49 (64.6%) than among individuals aged 50 to 64 (52.0%). The rates rose for younger individuals post-Covid, but remained steady among the older workers.

We measure working from home based on responses to the QLFS question which asks, "In your main job, do you work mainly: in your own home, in the same grounds or buildings as your home, in different places using home as a base, or somewhere quite separate from home". For all responses but "somewhere quite separate from home", we code individuals as working from home. As shown in Table 1, working from home was relatively rare prior to Covid; only 12% of non-disabled respondents were working from home regularly in 2018 and 2019, and 14% of disabled respondents, 10% of younger respondents, and 17% of older respondents. Working from home rates grew during the pandemic, increasing by 19 percentage points for the non-disabled, 18.5 for the disabled, 21 for younger workers and 15 for older workers.

Because the choice to work from home may be endogenous, we use the pre-Covid working from home index from Dingel and Neiman (2020) to measure what occupations can be done from home and which cannot. We specifically use the UK-version of this index developed by De Fraja et al. (2021). Prior to Covid, the average index was 0.435 among non-disabled individuals, 0.39 among disabled respondents, 0.44 among younger respondents, and 0.41 among older respondents. These averages rose for all groups post-Covid. Figures 2 and A2 show how these WFH rates and the average by De Fraja et al. (2021) index have changed over time.[3]

robustness exercise, we test how sensitive our results are to including individuals with a cognitive disability in Table 4. Post-Covid the share whose primary health condition was physical rose slightly, and the share with a cognitive health issue declined. For those with a health condition, individuals are also asked what activities are limited by their condition, with 76% reporting that it limits their work in some way in the pre-Covid period (either the amount of work they can do or the type of work they can do). Post-Covid, the share with a work-limiting disability fell slightly as newer disabled individuals had less-severe conditions. Considering the sample of individuals split by above age 50 and below, we find lower rates of physical and cognitive disabilities on average among younger individuals, and the share of disabilities that are work-limiting also increases with age.

[3] See Appendix Figure A1 for the distribution of change in WFH rates at the occupation-level.

WFH take-up is unlikely to be uniform, as groups may face distinct costs and benefits associated with remote work. Understanding the representation of these groups within the sample of disabled (or older) individuals employed full time provides important context for interpreting subsequent analyses and assessing whether observed patterns in WFH uptake reflect underlying changes in group composition. The descriptive statistics presented below summarise the characteristics of the sample and the relative shares of the key groups considered throughout the paper. Table 1 presents descriptive statistics for our full-time employed sample for non-disabled/disabled and ages 18-49 (younger) and ages 50-64 (older), split into two sub-samples: pre- and post-Covid, covering 2018-2019 and 2023-2024 respectively. Full-time work is defined according to the ONS definition, meaning an individual is working 30 hours per week or more.[4] Prior to Covid, the average age in our non-disabled sample is 42 years old, with 39% of the sample being female, 89% of the sample is white, and 38.5% were university educated. The disabled sample is older at 46 years old and more likely to be female (46.5%), more white (90%), and less university educated (30%). After the pandemic, the demographics of the disabled sample remained similar, with only percent female (50%) and university education rates (39%) rising. Similar post-Covid changes occur within the non-disabled sample (with female at 41% and university educated at 48%).

When we consider the samples by age, we find the pre-Covid age 18 to 49 sample is 41% female, 36 years old, 88% white, and 42% university educated. The pre-Covid age 50+ sample is 39% female, 56 years old, 92.5% white, and 27% university educated. Post-Covid, the share female increases slightly for both age groups (44% and 41% respectively), the average age is highly similar, the share white falls slightly (84% and 91% respectively), and the share university educated rises by 10 percentage points for the younger sample and 8 percentage points for the older sample.

Additional variables include commute time which is measured in minutes (with commutes longer than 3 hours top-coded at 180 minutes, and we set commute times for individuals who primarily work from home, and were thus not asked about commute times, at zero), usual hours worked in a week, and hourly wage (calculated as gross weekly pay divided by usual hours worked). Each of these additional outcomes are ultimately converted to be a pre- and post-covid growth rate, in order to be consistent with our employment measure.

Empirical Framework

We are primarily interested in whether rising rates of remote work in the UK has led to increased employment for individuals with a disability or older individuals. To test this, we use occupation-level

[4] We present the sample sizes of adults 18 to 64 with a disability by health problem by year in Table A1. For information on all disabilities for the full sample see Appendix Table A2.

data from the QLFS and follow the empirical strategy in Bloom et al. (2026).[5] We aggregate observations to the occupation level using three-digit occupation codes from the UK's Standard Occupational Classification (SOC) 2010 system. We combine observations from small occupations if they have fewer than 20 observations in either the pre-Covid period or the post-Covid period. We are left with 87 occupations for disabled workers and 90 occupations for older workers.

$$\%\Delta Emp_j^d = \beta \Delta WFH_j^{nd} + \gamma f\left(\Delta Emp_j^{nd}\right) + \Delta X_o \delta + \varepsilon_j \qquad [1]$$

Equation 1 presents our OLS regression model. For illustrative purposes, we will discuss the disabled workers version, but the model for older workers follows the same structure. Our outcome variable $\%\Delta Emp_j^d$ is the percent change in disability employment in occupation *j*. The superscripts *d* and *nd* indicate "disabled" and "non-disabled" respectively. For each occupation, we calculate this change in employment as the number of disabled individuals employed post-Covid minus the number of disabled individuals employed pre-Covid divided by the number employed pre-Covid in an occupation. The occupation-level estimates capture changes in the distribution and level of employment across occupations. They may reflect both net entry into employment and reallocation toward occupations in which WFH expanded. To account for differences in the size of occupations, which influences how precisely $\%\Delta Emp_j^d$ is measured, we weight the regression by the inverse of the estimated variance of $\%\Delta Emp_j^d$, to give more weight to larger, more precisely estimated occupations. We bootstrap 500 iterations of the $\%\Delta Emp_j^d$ calculation to determine the estimated variance.

We regress $\%\Delta Emp_j^d$ on the change in non-disabled WFH (ΔWFH_j^{nd}) opportunities in the occupation between pre-Covid (2018-2019) and post-Covid (2023-2024). Using occupation-level WFH rates for disabled workers directly could introduce reverse causality, as disabled workers may have stronger preferences for remote work and may bargain for it as part of their "reasonable accommodations" under the Equalities Act. If so, observed increases in WFH among disabled workers could partly reflect changes in disability employment itself. To account for this possibility, we use the WFH rates of non-disabled (*nd*) workers (or younger workers when studying older workers) as a proxy for how WFH rates have changed. Since WFH is not an automatic right in the UK, while still an endogenous choice that workers are making, the rise among non-disabled workers represents a valid proxy that substantially reduces the concerns of reverse causality.[6] Because changes in the disability employment gap may be

[5] Similar to Bloom et al. (2026) we focus primarily on employment outcomes, however we also consider effects on outcomes including commute times, hours worked, and educational attainment. We also run a series of additional robustness checks to ensure our results are not driven by subjective empirical choices such as reweighting vs the inclusion of controls, the approach to reweighting, and different functional forms for labor market tightness. Unlike Bloom et al. (2026), we expand our analysis to also consider older adults, since they are a similarly vulnerable population that may be impacted by th rise in work from home opportunities.

[6] We find that our OLS and IV results are quite similar, indicating that reverse causality may not be a substantial concern in our setting.

due to labour market tightness (i.e., tighter labour markets increase competition and reduce discrimination), we control for the change in employment for non-disabled workers using a third-order polynomial $f\left(\Delta Emp_j^{nd}\right)$; in robustness checks we instead control for linear and quadratic labour market tightness in Appendix Table A3.

To account for changes in the demographic composition of disabled workers across time, we reweight the microdata using inverse probability weights. Specifically, we estimate a regression model predicting an indicator for being observed in 2023-2024 (the post-Covid period) as a function of age, gender, race, education, and region among disabled individuals. We then construct inverse propensity weights equal to the overall share of post-period observations divided by each individual's predicted probability of being in the post-period, and multiply these by the original survey weights. As a robustness check (deviating from Bloom et al. (2026)), we replace the sample reweighting with controls for how the observable characteristics of individuals in an occupation have changed to observe how changes in sorting of individuals across occupations drives the results. ΔX_o controls for change in the share female, average age, share university educated, share exposed to furlough, and share in each region. Heteroskedastic robust standard errors are used.

Because the measure of working-from-home among the non-disabled (or younger) workers, ΔWFH_{oG}, may not be exogenous, we additionally use an instrumental variable approach as our main specification. Our estimates of β may be biased by additional reverse causality. If minority employment falls in an occupation (say, due to discrimination, automation, or health risks), majority workers may *substitute into WFH* in those jobs. Thus, ΔWFH_{oG} may partly reflect minority outcomes. β may also be biased by unobserved omitted variables. Occupation-level shocks (e.g., industry downturns, policy changes, technology adoption) may simultaneously drive both majority WFH and minority employment changes. Finally, β may be biased by measurement error from imputation (rolling forward responses), misreporting of WFH rates, and vagueness around remote work definitions versus hybrid working. If there is random noise in our measure of working-from-home, the OLS estimates will be biased toward zero.

$$\Delta WFH_j^{nd} = \mu + \rho I_j + \delta f(\Delta Emp_j^{nd}) + \upsilon_o$$

[2]

$$\%\Delta Emp_j^{d} = \alpha + \beta \Delta \widehat{WFH}_j^{nd} + \gamma f(\Delta Emp_j^{nd}) + \varepsilon_o$$

To solve these potential problems, we instrument for changes in work-from-home patterns in an occupation with a pre-Covid defined measure of WFH ability within an occupation (Dingel and Neiman, 2020). I_o is an occupation's work from home index (Dingle and Neiman 2020), which has been translated from US occupations code to UK occupation codes by De Fraja et al. (2021). The 2SLS

estimation identifies changes in working-from-home rates in an occupation which are due to the ease with which the job can be done from home, not on the individual choices of individuals to work from home or decisions by firms to allow employs to work from home. In addition to $\%\Delta Emp_j^d$, we are also able to use this IV framework to explore the effects of WFH on commute time and usual hours worked.

Results

Main Results

Table 2 provides OLS results for the effects of a change in the occupation-level WFH rates for non-disabled (younger) individuals on the occupation-level percent change in disability (older) employment as in equation [1]. Panel I, Column 1, shows that a 1 percentage point increase in the change in non-disabled work from home increases the employment growth rate for disabled by 0.57%. Reweighting the samples to account for changes in composition post-Covid, increases the estimate to 0.93%. Adding cubic controls for the change in employment among non-disabled workers cuts the magnitude in half to 0.48%, while adding controls for worker observables directly, rather than composition reweighting, decreases the magnitude again to 0.20%. The estimates are positive across specifications, although their magnitude is sensitive to how changes in occupational employment and worker composition are addressed.

The size of these estimates is economically meaningful. The WFH rate among non-disabled workers increased by approximately 19 percentage points between the pre- and post-Covid periods. Applying the coefficient from Column (3) implies predicted growth in disabled full-time employment of approximately 9.2 percent, while applying the more conservative estimate from Column (4) implies predicted growth of approximately 3.9 percent. Full-time employment among disabled people rose by 3.2 percentage points from a pre-Covid base of 34.4 percent, equivalent to an increase of approximately 9.3 percent. An illustrative comparison therefore suggests that expanded WFH opportunities could account for between 42 and 99 percent of the observed rise in full-time employment among disabled workers, depending on the specification used.[7] These calculations should not be interpreted as a formal decomposition, since they apply occupation-level coefficients to the aggregate increase in WFH and may capture both net employment growth and movement of disabled workers toward occupations in which WFH expanded, but are a useful back-of-the-envelope calculation of the role of WFH in the employment growth of disabled workers.

[7] WFH rates among non-disabled individuals rose 19.3 percentage points (Table 1 Column 2 minus Column 1). This is multiplied by our point estimate from Column (3) of 0.48, which equals 9.26. Full-time employment among disabled individuals rose 3.2 percentage points from a base of 34.4%, a 9.3% increase. 9.26/9.30=0.99. The effect is cut in half, to 42% if we use the point estimate from Column (4) of 0.20 (0.20×19.3=3.86, 3.86/9.30=0.42).

We see a similar pattern for older workers, in which a 1 percentage point increase in the change in younger work from home increases the employment growth rate for older workers by 0.40% in Panel II, Column (1). Composition reweighting in Column (2) increases the estimate to 0.52%. Adding cubic labour market tightness controls in Column (3) decreases the point estimate to 0.26%, and adding controls for worker observables rather than composition reweighting decreases the magnitude to 0.20%. The interpretation of the older-worker estimates differs somewhat from that of the disability estimates. Because aggregate full-time employment among older workers did not rise between the pre- and post-Covid periods, the positive occupation-level relationship does not necessarily indicate substantial net entry into employment. Instead, it may reflect reallocation of older workers from occupations with relatively little WFH growth toward occupations in which WFH expanded, greater retention within those occupations, or delayed retirement.

Taking the specification in Column (3) as our base specification in Table 3, we run 2SLS using the De Fraja et al. (2021) version of the Dingel and Neiman (2020) WFH index to instrument for change in WFH in an occupation, as with equations [2]. Panel I shows strong first stages for both disability and age samples, with F-statistics over 40 for each.[8]

Panel II reports the 2SLS estimates. For workers with physical disabilities, the coefficient of 0.93 in Column (1) reweights by occupational composition. This result implies that a one-percentage-point increase in WFH induced by an occupation's pre-Covid remote-work feasibility increases full-time employment among physically disabled workers in that occupation by approximately 0.93 percent. The estimate is statistically significant and is close to the approximately 1 percent effect reported for the United States by Bloom et al. (2026), despite differences between the two countries in disability measurement, occupational composition, and labour-market institutions. Using the observed increase in WFH, this IV estimate implies a large increase in disabled full-time employment in occupations where remote-work opportunities expanded. The estimate is sufficient to explain the aggregate increase in disabled full-time employment and, in addition, is consistent with movement of disabled workers from occupations with lower WFH growth toward occupations with higher WFH growth. Using an alternative specification with direct worker controls instead of reweighting in Table 2, Column (4), produces a smaller IV estimate of 0.37. An analogous back-of-the-envelope calculation suggests that approximately 77 percent of the increase in disabled full-time employment could be associated with expanded WFH opportunities under this more conservative specification.

[8] As would be expected given our first-stage F-statistics, results are robust to using VtF confidence intervals, as well as Anderson-Rubin confidence intervals.

For older workers, our preferred IV estimate in Column (3) is 0.38. A one-percentage-point increase in WFH induced by pre-Covid remote-work feasibility is associated with approximately 0.38 percent greater full-time employment growth among workers aged 50 to 64 in the occupation. The estimate is smaller than the disability effect but remains statistically and economically significant. As with the OLS estimates, the absence of aggregate growth in older full-time employment suggests that the IV result is likely to reflect retention, delayed labour-force exit, or movement toward occupations with expanding WFH opportunities rather than substantial net employment creation.

Robustness Checks and Heterogeneity

There may be concerns about whether our results are robust to alternative choices of universe. Table 4 estimates equations [2] using different samples. For disabled workers, the estimates on alternative samples range from 0.60% to 0.98%, with many estimates similar in magnitude to the baseline sample. For older workers, the estimates are even more stable, ranging from 0.39% to 0.46%.

If we vary our universe to include different groups of disabled workers, the estimates remain significant. Our baseline estimates restricted the universe to full-time work because that is where the rise in WFH work was concentrated in the UK. If we include part-time work, defined as working less than 30 hours per week, in the universe, the magnitudes for disabled results diminish to 0.60% in Panel 1, Column 1. Both the point estimates and the first-stage F-stat decline, suggesting that part-time work is less sensitive to the rise in WFH opportunities, since we observe our results being attenuated towards zero. The results are similar to our baseline estimates when including cognitive disabilities, not just physical disabilities, as in Column 2. Finally, we restrict the universe to those with a work-limiting physical disability to test whether the effects are driven by those with the most severe disabilities. The magnitude is similar at 0.84%, but less significant than the baseline universe, which includes all disabilities regardless of how they affect the amount or type of work an individual can do.

We find limited evidence of heterogeneity in the effect of WFH. For disabled workers, we may be picking up a partial correlation between age and WFH in older individuals given that disability increases with age. However, when we focus on the sample of adults who are age 18-49, as in Column 4, we see very similar results (0.91%). Looking just at full-time workers aged 50-64, as in Column 5, reduces significance, but the magnitude remains similar at 0.85%. Thus, there is no evidence of intersectionality in the effect of WFH on employment for older disabled workers; older disabled workers do not experience meaningfully different employment effects from WFH than disabled workers overall. We also restrict our universe to just men or just women to account for the possibility that WFH may be differentially attractive to men and women due to differences in caring responsibilities. Disabled men

have a lower, marginally significant 0.63% in Column 6, while women's results are very similar to the main results (with the caveat that only 63 occupations are included with the female-only sample).[9]

Results are consistent given different universe choices for the older worker regressions in Table 3, Panel II whether including part time workers (coefficient of 0.30%) or defining older to be ages 50-75 (0.33%). Similarly, we find little evidence of heterogeneous effects by disability status or gender. If we look only at older workers who are disabled (although this result is not significant, and the number of occupations meeting our size threshold drops to 73),[10] or look only at non-disabled workers, the point estimates are very similar (0.46% vs. 0.44%). We also find very similar results if we limit the universe to just men (0.42%) or just women (0.42%), although the number of occupations drops to 87 for men and 74 for women. We do however see that most of the effects on older workers are found among those without college degrees (0.42%) compared to those with college degrees (-0.06%). This difference is consistent with older workers with college degrees already being represented in high WFH occupations and already delaying retirement.[11]

Additional Labour Market Outcomes

Rising rates of WFH among disabled and older workers led to a shift in where they did their work and how much they were paid for it. We would expect rising WFH rates to decrease average commute times mechanically. Table 5, Column (1) shows that a 1pp increase in WFH decreased average commute times to work by 1.54% in Panel I, and 1.24% for older workers in Panel II for each 1pp increase in WFH. Since WFH increases by 19 pp, this translates to an approximate 29% decline in commute times for disabled workers and 23% for older workers, which translates to about 5 minutes a day for disabled workers and 4 minutes a day for older workers.[12]

While the increase in WFH reduced the time individuals spent commuting, there was no change in the usual hours worked per week. Table 5, Column (2) shows that for both disabled workers and older workers, the increases in WFH did not significantly change the working hours of individuals. This

[9] We also investigated heterogeneity by university education, but the reduced sample sizes were too small to be informative. We present these results in Appendix Table A5. University-educated disabled workers see a large effect, while non-college-educated disabled workers see no significant effect of WFH. We find the opposite result for older workers; we find large effects for older individuals without an university degree, while there is no significant effect for university-educated individuals.

[10] Note that the reason that Panel II, Column 3 has a different magnitude than Panel I, Column 4 is because the control group in the former is younger workers while the control group in the latter is non-disabled workers.

[11] Pre-Covid, the average work from home index among older adults with a college degree was 0.62 while the average for non-college educated older workers was 0.33. Post-Covid, the average for older workers with a college degree rose by one percentage point to 0.63 while the average for those without a college degree increased by 4 percentage points to 0.37 (a 12% increase).

[12] The average commute time pre-covid was 16 minutes for disabled workers, and 15 minutes for older workers.

suggests that WFH primarily altered where work was undertaken, rather than the overall amount of labour supplied.

Recall that the predicted effects of increased work from home on wages for disabled and older workers were ambiguous, with potential increased productivity, decreased discrimination, and decreased costs leading to higher wages but lower reservation wages and increased competition for remote jobs decreasing wages. Table 5, Column (3) shows that a 1 pp increase in WFH decreases wages of disabled workers by 0.17% for both disabled workers and for older workers. This small, negative effect suggests that either lower reservation wages or increased competition for remote jobs were the dominant factor, outweighing any positive effects. That said, these results should be interpreted with caution as the sample size for the disability specification drops to 59 and the age specification to 75.[13]

The rise in WFH does not appear to be driven by the upskilling of individuals during the pandemic. We proxy for upskilling with a variable for at what age an individual finished schooling, with the assumption that individuals who upskill are currently in school or will have just finished school, leading to an older age for this variable. Table 5, Column (4) shows no change in the average age at which an individual finished schooling for disabled workers or older workers. Similarly, Table 5, Column (5) shows no change in the share of individuals in an occupations who have a university degree.

Summary and Conclusion

Despite structural and other labour market differences between the US and UK, the effect of increases in work from home on employment for disabled workers in the UK is only slightly smaller compared to those found in the US. We find that a 1pp increase in the change in WFH leads to a 0.93% increase in disabled full time employment rates, whereas the effect in the US resulted in a 1% increase. We also find a robust and steady increase in work for older workers with increased work from home rates in the UK; we find that a 1pp increase in the change in WFH leads to a 0.38% increase in older full time employment rates. These results suggest that the effect of work from home on employment for disabled workers crosses different settings and populations, and work from home may benefit other groups in the labour market as well.

The effects of WFH were felt in other labour market outcomes. Overall, increased WFH opportunities reduced commuting times without affecting usual hours worked for full-time workers, suggesting that it changed where individuals worked rather than the amount of labour supplied. WFH was also

[13] Bloom et al. (2026) do not use an IV specification to examine wages, instead using a triple interaction which we replicate in Appendix Table B3, Column (1). Using their back of the envelope calculations, they do find a negative effect on wages, albeit their effect is much larger than the one we observe, at -4.2%.

associated with small declines in wages for both disabled and older workers, suggesting that reservation wages were lower for WFH jobs. Finally, there was little evidence that these effects were driven by changes in educational attainment.

That our observed effects are not markedly different from those in the US for disabled workers suggests that the barriers WFH removes for disabled workers are potentially universal across labour market contexts. This convergence in results is perhaps surprising given the institutional differences between countries, but may reflect that the mechanisms driving the results are not specific to the American context. The modest attenuation in our estimates relative to Bloom et al. (2026) is consistent with the compositional and measurement differences noted above, but the similarity of the core finding across two quite different labour markets strengthens the case that the relationship between WFH and disability employment is robust and likely to generalize broadly.

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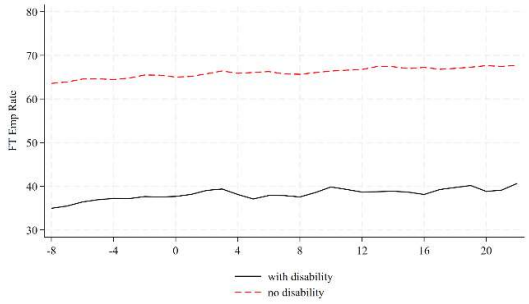
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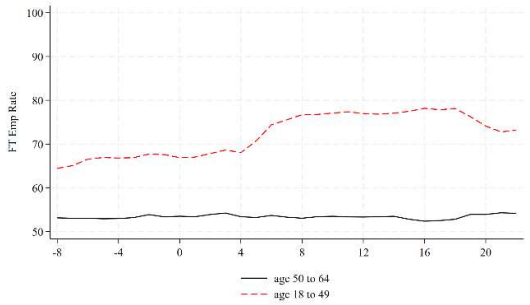
Figures

Figure 1: Change in employment over time

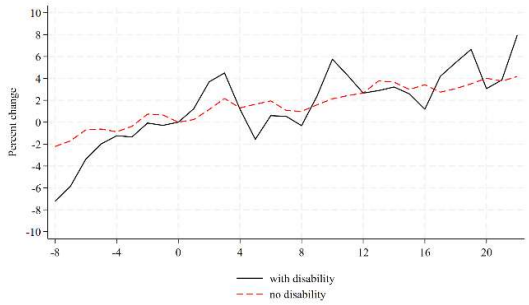
(a) Employment Rates by Disability



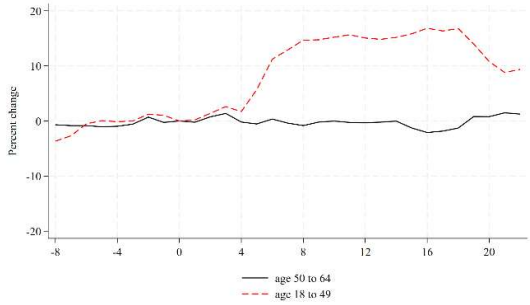
(b) Employment Rates by Age



(c) Relative Change by Disability



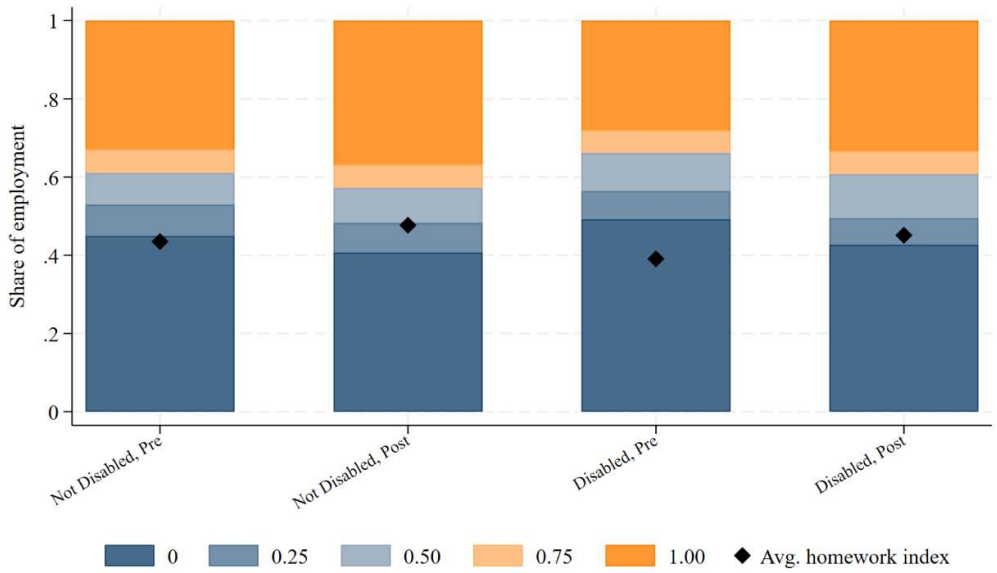
(d) Relative Change by Age



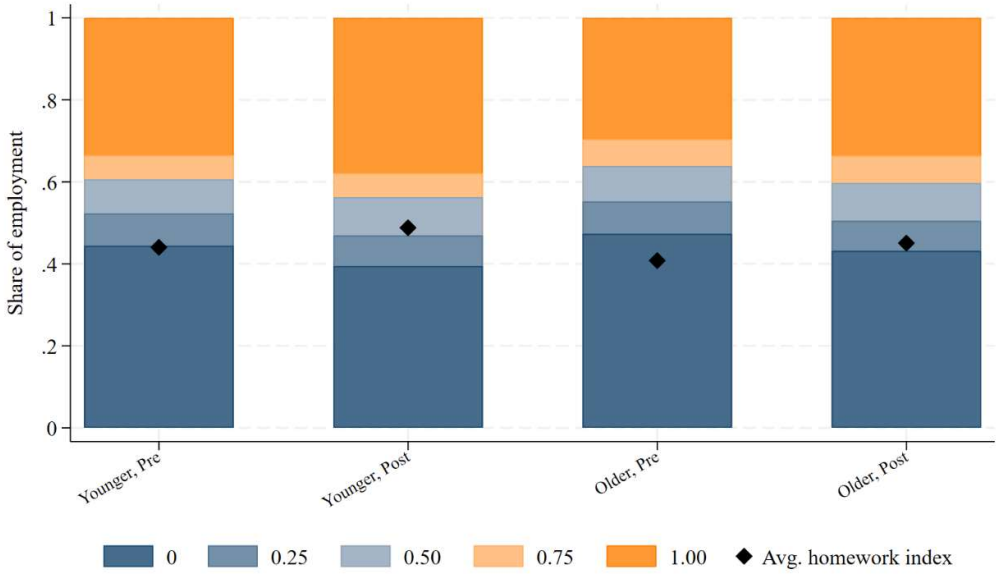
Notes: The top panel graphs the percent change in the employment relative to January 2019 while the bottom panel graphs the percent change in the employment relative to January 2019. Figures on the left compare those with and without a physical disability (18-64 years old) and figures on the right compare those above and below the age of 50 (18-64 years old). All figures use QLFS data.

Figure 2: Changes in Dingel and Neiman Work from Home Index over Time and by Group

(a) By Disability Status



(b) By Age Group



Notes: Figures present the share of full-time employment in each bin of the work from home index created by Dingel and Neiman (2020). The black diamonds represent the average work from home index for each group. Employment data are from the QFLS 2018-19 (pre-period) and 2023-24 (post-period).

Table 1: Descriptive Statistics of the Full-time Employed Sample

	Non-disabled		Disabled		Age 18 to 49		Age 50 to 64	
	2018-2019	2023-2024	2018-2019	2023-2024	2018-2019	2023-2024	2018-2019	2023-2024
Female	0.394	0.414	0.465	0.504	0.413	0.442	0.392	0.409
	(0.489)	(0.493)	(0.499)	(0.500)	(0.492)	(0.497)	(0.488)	(0.492)
Age	41.602	42.964	46.280	46.898	35.733	36.169	55.731	56.228
	(11.716)	(11.793)	(11.353)	(11.489)	(8.333)	(8.104)	(3.995)	(4.086)
White	0.888	0.857	0.904	0.891	0.877	0.841	0.925	0.911
	(0.316)	(0.350)	(0.295)	(0.312)	(0.329)	(0.366)	(0.264)	(0.285)
University	0.385	0.476	0.297	0.386	0.423	0.523	0.273	0.355
	(0.487)	(0.499)	(0.457)	(0.487)	(0.494)	(0.499)	(0.446)	(0.478)
Working-from-home	0.123	0.315	0.140	0.325	0.104	0.310	0.166	0.331
	(0.328)	(0.465)	(0.347)	(0.468)	(0.306)	(0.462)	(0.372)	(0.471)
WFH index	0.428	0.480	0.387	0.450	0.435	0.489	0.403	0.455
	(0.445)	(0.449)	(0.433)	(0.443)	(0.446)	(0.449)	(0.438)	(0.445)
Age 50 to 64	0.298	0.341	0.459	0.486	-	-	-	-
	(0.457)	(0.474)	(0.498)	(0.500)	-	-	-	-
Disabled	-	-	-	-	0.099	0.134	0.150	0.182
	-	-	-	-	(0.299)	(0.340)	(0.357)	(0.386)
Observations	209,244	102,112	22,153	14,721	166,920	80,191	74,796	43,583

Note: Data drawn from 2018, 2019, 2023, and 2024 QLFS. The sample has been restricted to individuals aged 18 to 64 to avoid those over state pension age. It is also restricted to include only those employed in full-time work. Individuals with cognitive health conditions are excluded. See the text for a description of disability and health coding.

Table 2: Effects of work from home on employment

	(1)	(2)	(3)	(4)
	I. Physical Disability			
Change in WFH	0.568***	0.817***	0.475*	0.200**
	(0.079)	(0.166)	(0.242)	(0.090)
Occupations	87	87	87	87
	II. Age			
Change in WFH	0.402***	0.516***	0.261***	0.200***
	(0.050)	(0.090)	(0.092)	(0.059)
Occupations	90	90	90	90
Composition reweighted		X	X	
Labour market tightness controls			X	X
Worker observable controls				X

* p<0.1 ** p<0.05 *** p<0.01. The dependent variable is the percent change in the number of individuals with a physical disability (or age 50 and older) who report being employed in an occupation between January 2018 to December 2019 and July 2023 to December 2024 in the QLFS. The independent variable is defined as the change in the fraction of individuals without a disability (or younger than age 50) who report they "worked from home" in 2023-2024 versus 2018-2019 using the location of work question from the QLFS. Since occupations differ in size, this affects how precisely the LHS variable is measured. Therefore, we weight the regressions by the estimated variance of the LHS variable, calculated using 500 bootstrap iterations. Occupation is defined using 3-digit standard occupational classification codes (90 occupations), merging occupations if there are less than 20 workers in a cell in Panel II. Robust standard errors are in parentheses. In columns (2) and (3), we reweight the data to account for compositional changes in the QLFS sample. This is done by predicting changes in the age, gender, race, college education. and region of residence of the respondents and adjusts the sample weights to account for these changes using the same method as Bloom et al. (2026). In columns (3) and (4), controls for labour market tightness are a third-order polynomial of the change in full-time non-disabled employment post versus pre covid. In column (4), we control for the change in worker observables directly in the OLS regression, rather than reweighting the sample.

Table 3: IV Effects of work from home on employment

	Physical Disability		Age	
	(1)	(2)	(3)	(4)
	I. First Stage			
WFH Index	30.911***	26.985***	32.463***	30.864***
	(4.262)	(4.226)	(3.727)	(3.544)
F-Stat	52.60	40.77	75.88	75.84
	II. 2SLS			
Change in WFH	0.928***	0.370***	0.384***	0.333***
	(0.299)	(0.119)	(0.127)	(0.074)
VtF Confidence Band	[0.360, 1.500]	[0.145, 0.597]	[0.142, 0.627]	[0.189, 0.478]
Composition reweighted	X		X	
Labor market tightness controls	X	X	X	X
Worker observable controls		X		X
Occupations	87	87	90	90

Note: * p<0.1 ** p<0.05 *** p<0.01. The second stage dependent variable is the percent change in the number of individuals with a physical disability (or age 50 or older) who report being employed in an occupation between January 2018 to December 2019 and July 2023 to December 2024 in the QLFS. The independent variable is defined as the change in the fraction of individuals without a disability (or younger than age 50) who report "worked from home" in 2023-2024 versus 2018-2019 using the location of work question from the QLFS. This is instrumented with an external measure of the remote work potential of each occupation, developed by Dingel and Neiman (2020) and modified for the UK context by De Fraja et al (2021). Since occupations differ in size, this affects how precisely the LHS variable is measured. Therefore, we weight the regressions by the estimated variance of the LHS variable, calculated using 500 bootstrap iterations. Occupation is defined using 3-digit standard occupational classification codes (90 occupations), merging occupations if there are less than 20 workers in a cell in panel (a). Robust standard errors are in parentheses. VtF confidence intervals (Lee et al. 2023) are reported in brackets. In columns (1) and (3), we reweight the data to account for compositional changes in the QLFS sample. This is done by predicting changes in the age, gender, race, and college education of the respondents and adjusts the sample weights to account for these changes using the same method as Bloom et al. (2026). In all columns, controls for labour market tightness are a third-order polynomial of the change in full-time nondisabled employment post versus pre covid. In columns (2) and (4), we control for the change in worker observables directly in the OLS regression, rather than reweighting the sample.

Table 4: IV Effects on employment for alternative samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I. Disabled Workers							
	FT + PT	FT incl. Cognitive Disabilities	Work Limiting Disability	Age 18-49	Age 50-64	Men	Women	
Change in WFH	0.604**	0.898***	0.838**	0.911***	0.852*	0.626*	0.984**	
	(0.267)	(0.305)	(0.405)	(0.334)	(0.496)	(0.344)	(0.417)	
First Stage F-Stat	45.67	56.79	47.65	48.26	29.92	62.06	41.22	
VtF Confidence Band	[0.101, 1.106]	[0.318, 1.482]	[0.071, 1.604]	[0.272, 1.542]	[-0.077, 1.877]	[-0.038, 1.281]	[0.200, 1.782]	
Occupations	87	87	79	71	80	73	63	
	II. Older Workers							
	FT + PT	FT age 50-75	Disabled	Not Disabled	Men	Women	University	No University
Change in WFH	0.298**	0.330***	0.464	0.438***	0.423***	0.422**	-0.068	0.417***
	(0.117)	(0.123)	(0.384)	(0.124)	(0.1552)	(0.185)	(0.324)	(0.136)
First Stage F-Stat	79.99	70.06	30.85	77.15	89.26	43.78	29.09	79.93
VtF Confidence Band	[0.073, 0.524]	[0.094, 0.565]	[-0.252, 1.236]	[0.199, 0.676]	[0.124, 0.721]	[0.075, 0.769]	[-0.669, 0.534]	[0.156, 0.677]
Occupations	90	90	73	90	87	74	79	88

* p<0.1 ** p<0.05 *** p<0.01. Regressions control for labor market tightness and are weighted by the inverse of occupation variance. Each column represents a separate sample of older or disabled adults. Part-time work is defined as working less than 30 hours per week. See table notes for Table 3 for details of data and estimation.

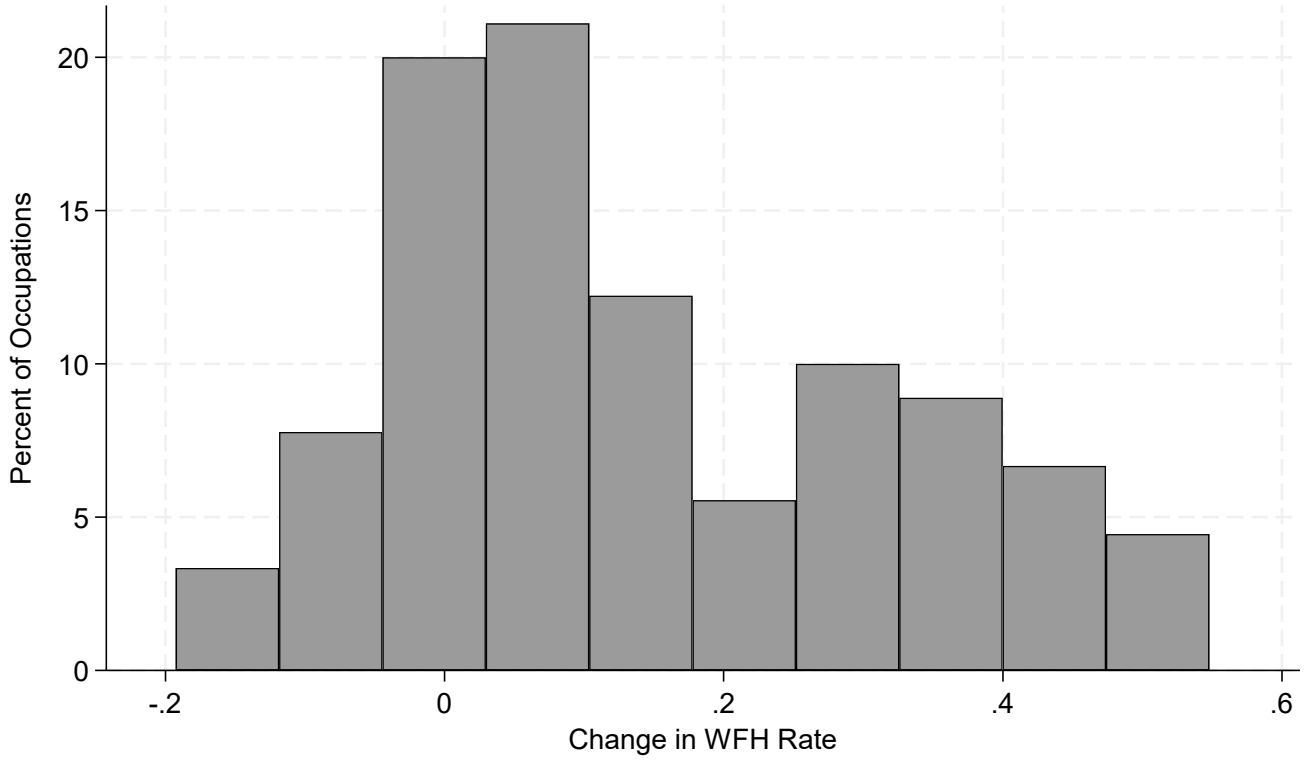
Table 5: IV effects on other outcomes

	Commute Time	Hours	Hourly Wage	Age Finished Education	University Degree
	(1)	(2)	(3)	(4)	(5)
			I. Disabled Workers		
Change in WFH	-1.542***	-0.012	-0.169*	0.038	0.133
	(0.234)	(0.020)	(0.094)	(0.028)	(0.225)
First-stage F-stat	27.41	88.69	56.4	82.13	35.83
Occupations	62	87	59	87	86
			II. Older Workers		
Change in WFH	-1.235***	-0.034	-0.174**	-0.018	0.104
	(0.157)	(0.024)	(0.075)	(0.018)	-0.219
First-stage F-stat	29.66	79.63	40.72	80.71	13.77
Occupations	83	90	75	87	87

Note: *** p<0.01, ** p<0.05, * p<0.1 . Robust standard errors in parentheses. Regressions include controls for labor market tightness and are weighted by the inverse of occupation variance. Each column relies on our base sample of older or disabled adults, but the outcome measures differ. All outcomes are measured as a percent change. See table notes for Table 3 for details of data and estimation.

Appendix A: Supplemental Figures and Tables

Figure A1: Distribution of growth in WFH



Notes: Data come from the QLFS. Change in the work from home rate is the share of workers in a 3-digit occupation who work from home in 2023-2024 minus the share who worked from home in 2018-2019.

Figure A2: WFH rates by year in the UK



Notes: Data come from the Quarterly Labour Force Survey. Sample is restricted to individuals aged 18 to 64 who are employed full-time. Dingel and Neiman's (2020) work-from-home index is assigned at the occupational level and reflects the average ability to work from home based on the distribution of occupations in which individuals are employed. Changes in the average index reflect changes in the composition of occupations individuals are employed in, not changes in the ability of a job to work from home.

Appendix Table A1: Primary Health Problems of Disabled Adults in the UK

	2019	2023	Total
No answer	918	83	1,001
Arms or hands	6,000	7,848	13,848
Legs or feet	8,648	5,398	14,046
Back or neck	10,805	4,883	15,688
Difficulty with seeing	963	781	1,744
Difficulty with hearing	833	644	1,477
Speech impediment	84	102	186
Skin conditions or allergies	822	876	1,698
Chest or breathing problems	5,106	3,382	8,488
Heart, blood pressure, or circulation	4,218	3,040	7,258
Stomach, liver, or kidney	4,125	2,279	6,404
Diabetes	2,587	1,644	4,231
Other problems or disabilities	9,548	4,826	14,374
Epilepsy	1,016	434	1,450
Depression or anxiety	13,814	7,916	21,730
Learning difficulties	1,684	429	2,113
Mental illness, phobia, or panics	5,196	2,187	7,383
Progressive illness n.e.c.	4,945	1,882	6,827
Autism	0	1,253	1,253
Total	81,312	49,887	131,199

Notes: Data come from the QLFS. Respondents are asked what health conditions they have. We consider the primary health problem to be the first one the individuals gives to the surveyor if they have reported multiple health conditions.

Appendix Table A2: Descriptive Statistics

	Non-disabled		Disabled		Age 18 to 49		Age 50+	
	2018-2019	2023-2024	2018-2019	2023-2024	2018-2019	2023-2024	2018-2019	2023-2024
Female	0.511	0.507	0.585	0.594	0.527	0.526	0.522	0.531
	(0.500)	(0.500)	(0.493)	(0.491)	(0.499)	(0.499)	(0.500)	(0.499)
Age	41.560	43.451	45.996	46.753	34.685	35.073	56.797	57.387
	(12.902)	(13.135)	(13.027)	(13.144)	(8.988)	(8.899)	(4.290)	(4.281)
White	0.869	0.849	0.897	0.894	0.848	0.820	0.924	0.915
	(0.337)	(0.358)	(0.305)	(0.308)	(0.359)	(0.384)	(0.266)	(0.279)
University	0.348	0.435	0.204	0.272	0.356	0.447	0.252	0.322
	(0.476)	(0.496)	(0.403)	(0.445)	(0.479)	(0.497)	(0.434)	(0.467)
Emp. full-time	0.650	0.670	0.344	0.376	0.626	0.657	0.520	0.513
	(0.477)	(0.470)	(0.475)	(0.484)	(0.484)	(0.475)	(0.500)	(0.500)
Physical Health Problem	-	-	0.722	0.753	0.180	0.213	0.392	0.418
	-	-	(0.448)	(0.431)	(0.384)	(0.409)	(0.488)	(0.493)
Cognitive Health Problem	-	-	0.267	0.245	0.079	0.098	0.052	0.051
	-	-	(0.442)	(0.430)	(0.269)	(0.297)	(0.222)	(0.220)
Work Limiting Disability	-	-	0.760	0.753	0.116	0.147	0.209	0.230
	-	-	(0.427)	(0.431)	(0.321)	(0.354)	(0.407)	(0.421)
Observations	332,962	158,079	81,312	49,887	270,562	123,390	145,969	85,925

Note: Data drawn from 2018, 2019, 2023, and 2024 QLFS. The sample has been restricted to individuals aged 18 to 64 to avoid those over state pension age. See the text for a description of disability and health coding.

Appendix B: Additional Robustness Checks

In this paper, we have followed the baseline methodology of Bloom et al. (2026) closely. Here, we present robustness checks of our results if we change the estimation strategy.

In Appendix Table B1, we examine the robustness of our results to alternative specifications of the polynomial used to control for labour market conditions. While Bloom et al. (2026) use a cubic polynomial, our findings are robust to using either linear or quadratic polynomials. Columns (3) and (6) reproduce the baseline specification presented in the main text, whereas the remaining report the corresponding estimates using linear and quadratic polynomials.

Using a linear polynomial to control for changes in employment among non-disabled workers (column 1) produces the largest OLS estimate and the smallest 2SLS estimate of the effect of WFH. As the order of the polynomial increases, the OLS estimates decline modestly, while the 2SLS estimates increase. For age, there is no clear pattern across specifications, although the cubic polynomial in column (6) yields the smallest estimate. Overall, the differences across specifications are modest, particularly when comparing the linear and quadratic specifications. These results indicate that our findings are not driven by the choice of polynomial used to control for occupation-specific labour market conditions.

In Appendix Table B2, we examine the robustness of our results to alternative weighting schemes used to account for changes in the population before and after the Covid-19 pandemic. Bloom et al. (2026) reweight only the population of disabled workers. We show that our findings are robust to two alternative approaches: reweighting the full QLFS sample or reweighting the treatment and comparison groups separately (i.e., disabled and non-disabled workers, and older and younger workers). Column (1) reproduces the baseline specifications presented in the main text, while Columns (2) and (3) report the results under these alternative weighting schemes.

Reweighting only the group of interest (Column 1) yields larger point estimates than reweighting the treatment and comparison groups separately (Column 3). Reweighting the groups separately also reduces the first-stage F-statistic. Reweighting the full sample (Column 2) produces smaller estimates than the baseline for the disability analysis but slightly larger estimates for the age analysis. The differences are modest for the age sample but more pronounced for the disability sample. Importantly, neither alternative weighting scheme changes the qualitative conclusions, indicating that our results are robust to the choice of reweighting approach.

In Appendix Table B3, we replicate the back-of-the-envelope triple interaction Bloom et al. (2026) use to estimate the change in wages and we also provide an additional robustness check by including controls for gender, region, race, and education and clustering at the three digit occupation level. We regress the individual-level data underlying Table 5 on a series of dummy variables for disability/older,

working in a high work from home occupation as defined by the De Fraja et al. (2021) index, and the post-Covid period. Our key parameter of interest is β_7 which captures the triple-interaction effect. Specifically, it measures whether the change over time in outcomes between high-WFH and low-WFH occupations differs for disabled (older) workers relative to non-disabled (younger) workers. β_7 identifies whether the post-Covid differential between high- and low-WFH occupations is larger (or smaller) for disabled (older) individuals than for their non-disabled (younger) counterparts. We include controls X_{ijt} for the same observable characteristics we used to composition reweight the occupation-level data for Equations 1 and 2 in Column (2). Standard errors are clustered at the 3-digit occupation-level in Column (2).

$$\begin{aligned} Y_{ijt} = \alpha &+ \beta_1 Group_i + \beta_2 HighWFH_j + \beta_3 Post_t + \beta_4\left(Group_i \times HighWFH_j\right) \\ &+ \beta_5(Group_i \times Post_t) + \beta_6\left(HighWFH_j \times Post_t\right) \\ &+ \beta_7\left(Group_i \times HighWFH_j \times Post_t\right) + X_{ijt}\delta + \varepsilon_{ijt} \end{aligned} \quad [3]$$

We find no statistically significant effect on hourly wages for either group, although the estimated coefficients are negative. These findings are consistent with increased opportunities for working from home leading to greater adoption of hybrid working arrangements among older workers, which may lengthen average commute distances as workers travel to the office less frequently. The inclusion of additional controls and clustering of standard errors does not qualitatively alter the wage results among disabled and older workers.

Appendix Table B1: Robustness check with different labour market controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Disability			Age		
	Panel I. OLS					
Change in WFH	0.452**	0.448**	0.401*	0.294***	0.292***	0.267***
	(0.211)	(0.210)	(0.222)	(0.096)	(0.095)	(0.094)
Non-group employment change (NGEC)	0.903***	0.996**	1.305***	0.376***	0.408***	0.537***
	(0.302)	(0.426)	(0.392)	(0.094)	(0.112)	(0.134)
NGEC^2		0.003	-0.015		0.002	0.003
		(0.011)	(0.010)		(0.003)	(0.002)
NGEC^3			-0.001**			-0.000**
			(0.000)			(0.000)
	Panel II. IV					
Change in WFH	0.808***	0.809***	0.816***	0.351***	0.355***	0.348***
	(0.276)	(0.275)	(0.279)	(0.121)	(0.120)	(0.121)
Non-group employment change	0.627*	0.679	0.880*	0.335***	0.362***	0.460***
	(0.321)	(0.430)	(0.456)	(0.108)	(0.122)	(0.153)
NGEC^2		0.002	-0.012		0.001	0.003
		(0.009)	(0.009)		(0.002)	(0.002)
NGEC^3			-0.001*			-0.000*
			(0.000)			(0.000)
Observations	87	87	87	90	90	90

Note: See Table 2 and 3 for notes on sample construction and estimation. Non-group refers to non-disabled for disability sample and younger for age sample.

Appendix Table B2: IV Effects on employment under alternative weighting schemes

	(1)	(2)	(3)
	I. Disabled Workers		
	Only disabled	All	Separately
Change in WFH	0.928***	0.891***	0.808***
	(0.299)	(0.273)	(0.297)
First Stage F-Stat	52.6	53.4	44.36
VtF Confidence Band	[0.360, 1.50]	[0.373, 1.414]	[0.248, 1.365]
Occupations	87	87	87
	II. Older Workers		
	Only older	All	Separately
Change in WFH	0.384***	0.421***	0.390***
	(0.127)	(0.123)	(0.126)
First Stage F-Stat	75.88	79.3	68.06
VtF Confidence Band	[0.142, 0.627]	[0.184, 0.657]	[0.149, 0.633]
Occupations	90	90	90

Note: See Table 3 for notes on the IV estimation. Column (1) repeats our baseline estimation where only disabled or older workers are reweighted. Column (2) reweights all observations together. Column (3) reweights all observations, but estimates the weights for older and younger individuals and disabled and non-disabled individuals separately.

Appendix Table B3: Triple interactions on hourly wage

	Hourly Wage	
	(1)	(2)
I. Disabled Workers		
Group x Post x High WFH Occ	-0.156	-0.124
	(0.389)	(0.355)
Observations	75,343	68,967
II. Older Workers		
Group x Post x High WFH Occ	-0.149	-0.222
	(0.260)	(0.372)
Observations	79,416	72,775
Controls		X
Cluster on 3-digit occupation		X

Note: * p<0.1 ** p<0.05 *** p<0.01. Standard errors clustered on 3-digit occupation code in Column 2. Controls include main effects, interacted main effects, and controls for gender, region, race, and education.

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