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

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Abstract: Remote work is often 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. Following Bloom et al. (2025), we test the effects of remote work on employment for these two groups using the pandemic's increase in work from home rates as a quasi-experiment. We compare 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. We then instrument using pre-pandemic remote work scores from Dingle and Neiman (2020). We find significant evidence that rising WFH increases employment of disabled and older workers in the UK. We additionally find decreases in commute time and hours worked for both groups, but no effect on hourly wages and mixed results on unemployment duration.

Keywords: disability, ageing, labour force, employment, United Kingdom

Introduction

Fifty-seven percent of the working age population that reported a work-limiting health condition in 2024 in the UK are not working (Mayfield, 2025a). Similarly, only 71.6% of those between the ages of 50 and 64 were 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 the disabled and older workers (e.g., Mayfield, 2025b). They 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 Department for Work & Pensions (2026), 28% of employees with health conditions worked from home as an adjustment, and 19% wished they could work from home more.

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

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(Ne'eman & Maestas, 2023; Bloom et al., 2025; 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., 2025). 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., 2022) 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 rates of remote working and employment gaps 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 early due to health or caring responsibilities. We are specifically interested in the effect of working from home (WFH) on employment outcomes for disabled and older workers. Using the pandemic-induced increase in WFH as a quasi-experiment, we compare the employment growth of workers with a physical disability in occupations with high growth in WFH among non-disabled workers to those occupations with lower growth in WFH among non-disabled workers. Similarly, for older workers, we use workers under the age of 50 as the control measure of WFH expansion across occupations. We instrument the rise in WFH using pre-pandemic remote work scores from Dingle and Neiman (2020) and De Fraja et al. (2021). We then use a triple interaction framework comparing disabled(older) to non-disabled(younger) in high/low WFH occupations before and after the pandemic to explore potential mechanisms for these differences.

Using our main IV results, we find that a 1 percentage point increase in change in WFH, as instrumented by the WFH index increases employment by 0.8% for disabled people 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 0.35%, suggesting that WFH also bolsters the employment of older people. Our results are robust to different choices of employment, definitions of disabilities, different age groups, and by gender. We also use the same IV strategy to look at other outcomes and find that WFH increases both 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. 2022; Bloom et al. 2025; 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

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., 2025; 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) improves employment outcomes for disabled people in the UK using similar non-casual 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 inequalities, but it is associated with better job satisfaction, mental health, and job control for all workers. 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 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, a recent Current Population Survey (CPS) questionnaire suggests that 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).

The work most similar to ours is Bloom et al. (2025) 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 disability employment 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. They find that wages for disabled workers fell by around 4 percentage points more in high-WFH occupations relative to non-disabled workers (a triple difference), which they interpret as evidence that increased labour supply, rather than increased employer demand, is the dominant mechanism driving higher disability employment.

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., 2022), 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 difference could go the other direction). 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 that perhaps the treatment effect in the UK is larger than that of the US.

UK Institutional details

Several institutional details between the UK and US may affect how work from home rates change employment outcomes. In the UK, disabled workers are disproportionately represented in occupations such as retail, which have lower remote-work feasibility (Schur et al., 2021; Ameri et al., 2022), potentially limiting the benefits of increased WFH. Definitions of disability in the UK datasets ask a different and broader set of questions to create disability definitions (DWP, 2025). For older workers, remote work is most common among those who are already unlikely to exit the labour force (Coombs et al., 2021), additionally potentially limiting the potential benefits of WFH.

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. In search models of the labour market, employment outcomes are determined by frictions that limit the ability of workers and firms to match efficiently, and by the presence of discriminatory firms (Black 1995). 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 search frictions, such as geographic constraints and commuting costs, which limit the set of firms from which they can receive offers. The presence of discriminatory firms in the market raises the monopsony power of non-discriminatory firms, which generates hiring and wage inequality.

The expansion of WFH opportunities can reduce search frictions by increasing the effective size of the labour market available to workers. When jobs can be performed remotely, workers are less constrained by commuting distance and can search for employment across a broader geographic area (Akan et al. 2025). In the search framework an ample supply of remote jobs increases the job offer arrival rate and improves workers' outside options. This leads to increases in labour supply, as well as increasing wages. These effects may be particularly important for disabled and older workers, for whom commuting may impose greater frictions.

WFH may also influence labour market outcomes through improvements in match quality. In search models with heterogeneous matches, improved compatibility between job characteristics and worker constraints increases the value of employment relative to non-employment, further raising job acceptance rates and employment stability. Greater flexibility in work location and scheduling allows workers to better manage health conditions, medical appointments, or caring responsibilities, which increases the match quality for remote jobs relative to non-remote. These mechanisms imply that WFH may increase employment along both the extensive margin, by drawing additional individuals into the labour force, and potentially the intensive margin, by allowing workers to work more hours and obtain full-time jobs. Higher-quality matches may also generate higher wages, since the surplus from the match is larger and part of that additional surplus accrues to the worker.

WFH reduces the costs of employment, primarily through reducing or eliminating the cost of commuting (Pabilonia and Vernon, 2025). This lowers the reservation wage and raises the value of employment relative to non-employment. This leads to workers being willing to accept a larger share of the job offers they receive. As a result, employment increases and unemployment durations fall. Because workers accept job offers more readily, the probability that a job offer results in a match rises, which increases the job-finding rate. In equilibrium search models, this also tends to increase job creation by firms because vacancies are filled more easily. However, the reduction in reservation wages

can place downward pressure on wages, since workers are willing to accept lower pay when the overall cost of working is lower.

Our main focus in the paper is the effect on employment. To summarize the above, from the supply side, we would expect employment of older and disabled workers to increase because of the reduced costs of working given reduced commuting costs and potentially no longer having to duplicate accommodations in both the work and home environment. Expanded geographic reach and better control of the work from home environment may also increase employment. From the demand side, employers may demand more disabled when WFH rates go up because they can shift accommodation costs to workers, making them less expensive than when they work in the office. These together lead to an unambiguous increase in employment for occupations with high growth in WFH relative to low growth WFH occupations for disabled and older workers compared to non-disabled and younger workers.

The effect of increased WFH on the remaining outcomes are more ambiguous. For wages, from the supply side, reduced costs of working should decrease workers' reservation wages. Similarly, increased competition from a wider geographic area will also decrease wages. On the other hand, better control of the environment could increase worker productivity, leading to higher wages. From the demand side, as the costs of accommodation shift from firms to workers, firms may be willing to pass on some of that decreased cost through wages. Similarly, decreased discrimination (from not, for example, being able to see a physical disability) would increase wages.

The effect of increased WFH also has ambiguous effects on unemployment duration. From the supply side, decreased costs of working would decrease unemployment duration, but increased competition for high WFH jobs may increase it. From the demand side, decreased discrimination could decrease unemployment duration.

Data and Descriptive Statistics

We use data from the Quarterly Labour Force Survey (QLFS) from the United Kingdom (ONS 2025). The QLFS, conducted by the Office for National Statistics (ONS), provides data on the labour market, including economic activity and job characteristics. The survey uses a random sample of private households, drawn from the Postcode Address File, ensuring a broad geographic representation. Households are surveyed for five consecutive quarters (waves). 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.

The Quarterly Labour Force Survey (QLFS) in the UK measures disability using a series of questions based on the Equality Act 2010 definition and the Government Statistical Service (GSS) harmonised standards. 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 sample, we define as disability as one if an individuals is disabled under the Equality Act 2010 definition and their health conditions are only physical in nature, and zero if not disabled under the Equality Act 2010 definition. Individuals who are disabled with a cognitive disability only are excluded in the disability sample (but not in the age sample).

Figure 1 presents the evolution of the share of individuals employed full-time, as the percent change relative to 2019Q1. Figures 1a and 1b report the results for disabled vs. non-disabled individuals, and Figures 1 c and 1d report the results for younger vs. older individuals. Full-time employment was more common among non-disabled individuals (65.0%) than among disabled individuals (34.4%) pre-COVID. The rate rose for both groups post-Covid, with a slightly larger increase among disabled individuals.

Table 1 presents the descriptives of 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, or 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. Note that in this table we use the definitions of disability that we use in the paper; to get information on all disabilities for the full sample see Appendix Table A2.[2] In our baseline specifications, we follow Bloom et al. (2025) and focus on individuals with a physical disability, since autism and ADHD were not measured pre-Covid in the QLFS.[3] Prior to Covid, the average age in our non-disabled sample is 42 years old, with 39% of the sample being female,

[2] We present the sample sizes of adults 18 to 64 with a disability by health problem by year in Table A1.

[3] Approximately 20% of the population had a disability pre-Covid and 24% had a disability 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 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 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.

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.

We measure working from home based on responses to the QLFS question asking, "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. Working from home was relatively rare prior to Covid; only 12% of non-disabled respondents were working from home regularly in 2018 and 2019, 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 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). We aggregate the 4-digit Standard Occupational Classification (SOC) for workers to a 3-digit Minor Group level. There are 90 3-digit SOC groups of which 89 are observed in the QLFS during our period, but we merge several near-neighbour occupations that have fewer than 20 disabled individuals employed in that occupation. Prior to Covid, the average index was 0.43 among non-disabled individuals, 0.39 among disabled respondents, 0.435 among younger respondents, and 0.40 among older respondents. These averages rose for all groups post-Covid. Figure 2 shows how these WFH rates and the average Dingel and Neiman (2020) index have changed over time.[4]

Additional variables include commute time which is measured in minutes (with commutes longer than 3 hours top-coded at 180 minutes, and individuals who work from home set given a zero), usual hours

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

worked in a week, hourly wage (calculated as gross weekly pay divided by usual hours worked) and unemployment duration greater than a year which is measured for people who are unemployed during the time of the quarterly survey. 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 data from the QLFS. 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 pre-Covid minus the number of disabled individuals employed post-Covid divided by the number employed pre-Covid in an occupation. 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 1,000 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 follow Bloom et al. (2025) and 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 will not suffer from reverse causality[5]. Because changes in the disability employment gap may be 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, following Bloom et al. (2025). Specifically, we estimate a regression model predicting an indicator for being observed in 2023 (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, 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.

$$\Delta WFH_j^{nd} = \mu + \rho I_j + \delta \Delta Emp_j^{nd} + \upsilon_o \qquad [2]$$

$$\%\Delta Emp_j^{d} = \alpha + \beta \Delta \widehat{WFH_j^{nd}} + \gamma \Delta Emp_j^{nd} + \varepsilon_o$$

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

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

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.

We are unable to look at the effects of unemployment duration or wages using our IV framework, and instead move to a triple interaction framework. [6]

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

Here we regress individual outcomes for unemployment duration and wages 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. We include controls X_{ijt} for the same observable characteristics we used to composition reweight the occupation-level data for Equations 1 and 2. Standard errors are clustered at the 3-digit occupation-level.

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 workers relative to non-disabled workers. β_7 identifies whether the post-Covid differential between high- and low-WFH occupations is larger (or smaller) for disabled individuals than for their non-disabled counterparts. For example, if the outcome variable is commute time and $\beta_7 < 0$, this implies that commute times declined more in high-WFH occupations than in low-WFH occupations for disabled workers, and that this relative decline was larger than the corresponding change observed among non-disabled workers. Thus, a negative estimate would indicate that the expansion of remote work disproportionately reduced commute times for disabled workers.

[6] We are unable to use wages in our instrumental variables framework because only about a third of respondents answered the wage question in the QLFS, making the cell sizes too small for many cells and the regressions highly sensitive to how these small cells are treated. The triple interaction is less problematic because all high and low WFH occupations are grouped together, respectively.

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 0.82%. Adding cubic controls for the change in employment among non-disabled workers cuts the magnitude in half to 0.40%, while adding controls for worker observables directly, rather than composition reweighting, decreases the magnitude again to 0.20%. Given the 19-percentage point increase in WFH employment, and our observed 0.20% effect size, we would expect full-time employment of disabled individuals to rise 3.86% during the pandemic. Thus, a back-of-the-envelope calculation suggests that 82% of the rise in full-time employment observed among disabled workers can be explained by rising WFH opportunities.[7]

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 0.46%. Adding cubic labour market tightness controls in Column (3) decreases the point estimate to 0.27%, and adding controls for worker observables rather than composition reweighting decreases the magnitude to 0.18%. Because we observe a decrease in full-time employment post-Covid, expanded WFH opportunities did not draw new people into the labour market. This implies that the growth in high-WFH occupations is a reallocation of workers across occupations, either amongst individuals already employed or through reductions in 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 groups, with F-statistics over 55 for each.[8] Our 2SLS for disability finds results which are larger than observed in the OLS results, with a magnitude of 0.79 for disability and 0.35 for age. Because the 2SLS estimates are larger than the OLS estimates, they imply that reallocation across occupations is

[7] WFH rates among non-disabled individuals rose 19.3 percentage points (Table 1 Column 2 minus Column 1). This multiplied by our point estimate of 0.398 equals 7.68. Full-time employment among disabled individuals rose 3.2 percentage points from a base of 34.4%, a 9.3% increase. 7.68/9.30=0.826. The effect is cut in half, only 42% if we use the point estimate from Column (4).

[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, to account for the possibility the Dingel and Neiman (2020) WFH index is a weak instrument.

larger for both disabled workers and older workers. For disabled workers, this implies that rising WFH opportunities increased full-time employment by 9% and on top of this, there was a significant reallocation from low WFH occupations to high WFH occupations.[9]

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 0.50% to 0.83%, with many estimates similar in magnitude to the baseline sample. For older workers, the estimates are even more stable, ranging from 0.29% to 0.41%.

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 0.50% in Panel 1, Column 1. Both the point estimates and the first-stage F-stat decline, suggesting that part-time work is indeed less sensitive to the rise in WFH opportunities, since we observe our results being attenuated towards zero. The results are very 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 0.73%, 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, the results are also very similar when decreasing the universe of age to include only 18-49 year olds, as in Column 3, to account for the fact that disability increases with age, and we may be picking up a partial correlation between age and WFH in the older individuals. Looking just at full-time workers aged 50-64, as in Column 4, reduces significance, but the magnitude remains similar at 0.75%. Thus, there is no evidence of intersectionality in the effect of WFH on employment for older disabled workers. 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, less significant 0.59% in Column 5, 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). The estimates do suggest that WFH opportunities were more beneficial for disabled women.

[9] If we use the same estimation strategy in Table 2, Panel I, Column (4) instead of Column (3), there is no role for reallocation. The back-of-the-envelope estimates show 75% of the increase in the increase in fulltime employment of disabled workers is potentially explained by rising WFH opportunities.

Results are remarkably consistent given different universe choices for the older worker regressions in Table 3, Panel II whether including part time workers (coefficient of 0.29) or defining older to be ages 50-75 (0.37). Similarly, we find very 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 (0.38 vs. 0.39). We also find very similar results if we limit the universe to just men (0.36) or just women (0.41), although the number of occupations drops to 86 for men and 74 for women.

Additional Labour Market Outcomes

We would expect that rising WFH rates would decrease commute times, as individuals who work exclusively from home have a 0 minute commute. Table 5, Column (1) shows that commute times for disabled workers in occupations with high WFH potential decreased by 2% in Panel I, and 1.7% for older workers in Panel II for each 1pp increase in WFH. Since WFH increases by 19 pp, this translates to an approximate 40% decline in commute times, which translates to about 8 minutes a day. We did not have a prediction on weekly hours worked, but they decrease by 0.63% for disabled workers and by 0.68% for older workers in Column (2) for a 1 percentage point increase in the WFH rate. Using the same back of the envelope calculations as earlier, this is approximately 5 hours less work for disabled and older workers due to increased WFH opportunities.[11]

We were unable to use our IV methodology to look at the effects on wages because of problems with small sample sizes, and with unemployment because cell sizes for many occupations fall below our 20 individual threshold. Therefore, Table 6 reports the results of a triple interaction controlling for main effects and main paired effects as in Equation [3].

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 6 presents estimates of the differential change in hourly wages and unemployment spells greater than a year (conditional on being unemployed at the time of survey).

We find no significant change in the gap in wages between disabled workers and non-disabled workers in occupations with high WFH potential compared to the gap between disabled workers and non-

[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] A five-hour reduction in usual hours worked per week may seem large. The reduction may include time saved on commutes, shorter lunch breaks, and less time spent socialising.

disabled workers in occupations with low WFH potential (Panel I, Column (1)), though the point estimate is negative. We find a similar pattern of results for older workers in Panel II.

The predicted effects of increased work from home on unemployment duration for disabled and older workers were ambiguous, with potential decreased discrimination and decreased costs leading to shorter durations but increased competition and more selective searches for remote jobs increasing duration. We find a significant increase in the share of disabled workers unemployed for longer than a year compared to non-disabled workers in high WFH potential occupations. This suggests the shift towards WFH may have led disabled individuals to restrict their job search to these opportunities or increased competition for these jobs. However, we find a significant decrease in the share of older workers unemployed longer than a year compared to younger workers in high WFH potential occupations. This suggests WFH may have led to less discrimination against older workers or faster matching with jobs given a larger potential pool of jobs.

Summary and Conclusion

Despite structural and other labour market differences between the US and UK, the effect of work from home increases 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 0.79% 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 0.36% 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.

We find evidence that the effects of WFH were felt in other labour market outcomes. Overall, increased work-from-home (WFH) opportunities are associated with modest reductions in commute time, as well as declines in weekly hours worked for both disabled and older workers. While the effects on wages remain inconclusive due to data limitations and theoretically ambiguous forces, the evidence suggests no significant change in wage gaps between groups. However, WFH appears to have divergent impacts on unemployment duration: disabled workers in high-WFH occupations are more likely to experience long-term unemployment, possibly due to increased competition or narrower job searches, whereas older workers are less likely to remain unemployed long-term, indicating that WFH may help reduce age-related barriers in the labour market.

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 largely 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. (2025) 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.

References

Ameri, Mason, Douglas Kruse, So Ri Park, Yana Rodgers, and Lisa Schur. 2023. "Telework during the Pandemic: Patterns, challenges, and opportunities for people with disabilities." *Disability and Health Journal*, 16(2), 101406.

Bloom, N., Dahl, G.B. and Rooth, D.O. 2025. *Work from home and disability employment*. *AER-Insights*.

Coombs, Ngaire, Holly McLeod, and Angele Storey. 2021. "Living longer: impact of working from home on older workers." *Office for National Statistics.* https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/ageing/articles/livinglongerimpactofworkingfromhomeonolderworkers/2021-08-25 Last accessed 3/25/26.

De Fraja, G., Matheson, J. and Rockey, J. 2021. Zoomshock: The geography and local labour market consequences of working from home. *Covid Economics*, (64), pp.1-41.

Department for Work and Pensions (DWP). 2025. "The employment of disabled people: background information and methodology."

Department for Work & Pensions (DWP). 2026. "Is working from home working?" *House of Lords: Select Committee on Home-Based Working. Report of session 2024-2026*. *HL Paper 196.*

Dingel, Jonathan I., and Brent Neiman. "How many jobs can be done at home?" *Journal of Public Economics* 189 (2020): 104235.

Hansen, Stephen; Peter John Lambert; Nicholas Bloom; Steven J. Davis; Raffaella Sadun and Bledi Taska. 2023. "Remote Work across Jobs, Companies, and Space." *National Bureau of Economic Research Working Paper Series*, No. 31007.

Hoque, Kim, and Nick Bacon. "Working from home and disabled people's employment outcomes." *British Journal of Industrial Relations* 60.1 (2022): 32-56.

Jendrzejewski, Daniel and Ian Briedis. 2025. "Economic labour market status of individuals aged 50 and over, trends over time: September 2025." Department for Work and Pensions, UK Government.

Lee, David S., Justin McCrary, Marcelo J. Moreira, Jack R. Porter, and Luther Yap. 2023. "What to do when you can't use '1.96' Confidence Intervals for IV." *National Bureau of Economic Research Working Paper Series.* No. w31893.

Liu, Siyan, and Laura D. Quinby. 2024. "Has Remote Work Improved Employment Outcomes for Older People with Disabilities?" *Center for Retirement Research.* wp2024-12.

Mayfield, Sir Charlie. 2025. *Keep Britain Working Review: Discovery.* House of Lords, Select Committee on Home-Based Working. https://www.gov.uk/government/publications/keep-britain-working-review-discovery/keep-britain-working-review-discovery. Last accessed 3/24/26.

Mayfield, Sir Charlie. 2025b. *Keep Britain Working: Final Report.* House of Lords, Select Committee on Home-Based Working. https://www.gov.uk/government/publications/keep-britain-working-review-final-report/keep-britain-working-final-report. Last accessed 3/24/26.

Ne'eman, Ari and Nicole Maestas. 2023. How has COVID-19 impacted disability employment? *Disability and Health Journal,* 16(2):101429. doi: 10.1016/j.dhjo.2022.101429.

Office for National Statistics (ONS). 2025. *Quarterly Labour Force Survey, January 2018-December 2024*. [data collection]. *4th Edition.* UK Data Service. SN: 9323, DOI: http://doi.org/10.5255/UKDA-SN-9323-4

Pabilonia, Sabrina Wulff and Victoria Vernon. 2025. "How did the remote work revolution change our work and leisure time?" *Working Paper.*

Sanzenbacher, Geoffrey T. 2025. “Has remote work extended workers’ careers?” *Center for Retirement Research.* ib2025-9.

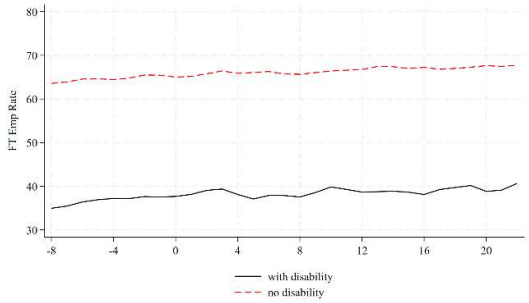
Schur, Lisa, Yana van der Meulen Rodgers, and Douglas L. Kruse. 2021. "COVID-19 and employment losses for workers with disabilities: an intersectional approach." *Available at SSRN 3788319*.

Tseng, Hsinyu (Samuel), and Douglas A. Webber. 2025. “Decomposing recent employment gains among disabled workers,” *Finance and Economics Discussion Series 2025-095*. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2025.095

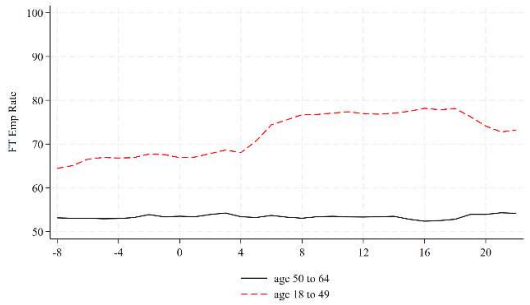
Figures

Figure 1: Change in employment over time

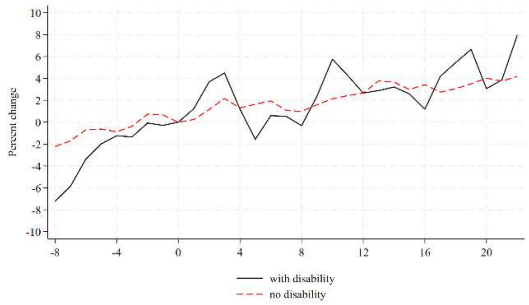
(a) Employment Rates by Disability



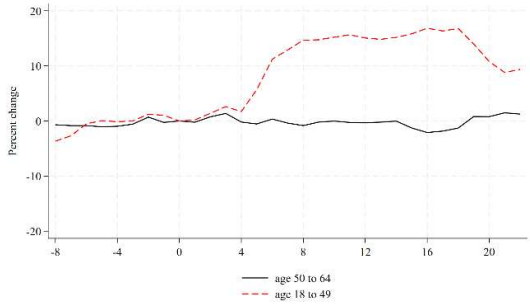
(b) Employment Rates by Age



(c) Relative Change by Disability



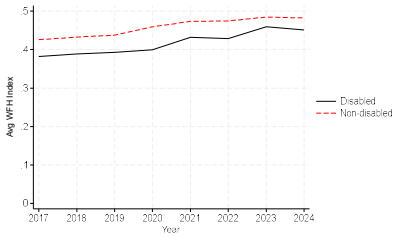
(d) Relative Change by Age



Notes: The left panel graphs the percent change in the employment relative to January 2019 for those with and without a physical disability (18-64 years old) using QLFS data. The right panel graphs the percent change in the employment relative to January 2019 for those above and below the age of 50 (18-64 years old) using QLFS data.

Figure 2: WFH rates by year in the UK

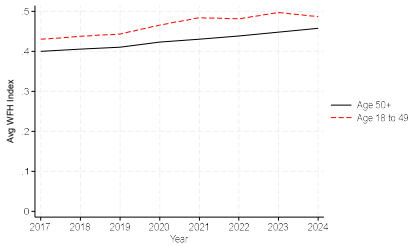
(a) WFH Index by Disability



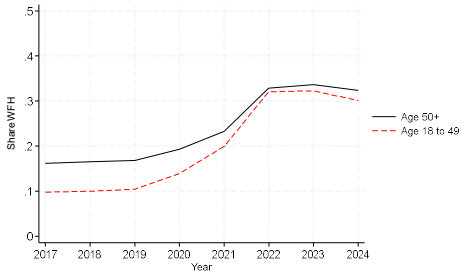
(c) WFH Rates by Disability



(b) WFH Index by Age



(d) WFH Rates by Age



Notes: Data come from the Quarterly Labour Force Survey. Sample is restricted to individuals age 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.

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	0.567***	0.818***	0.398*	0.200**
	(0.080)	(0.170)	(0.226)	(0.089)
Occupations	87	87	87	87
	II. Age			
Change in WFH	0.397***	0.461***	0.268***	0.181***
	(0.048)	(0.083)	(0.091)	(0.061)
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 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 who report "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. (2025). In columns (3) and (4), controls for labour market tightness are a third-order polynomial of the change in full-time nondisabled 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	Physical Disability	Age	Age
	(1)	(2)	(3)	(4)
I. First Stage				
WFH Index	31.242**	27.433***	32.486***	30.551***
	(3.956)	(3.631)	(3.955)	(3.183)
F-Stat	62.37	57.09	67.47	92.134
II. 2SLS				
Change in WFH	0.792***	0.366***	0.355***	0.337***
	(0.277)	(0.114)	(0.119)	(0.077)
VtF Confidence Band	[0.265, 1.325]	[0.150, 0.583]	[0.128, 0.583]	[0.190, 0.486]
Composition reweighted	X		X	
Labour market tightness controls	X	X	X	X
Worker observable controls		X		X
Occupations	87	87	90	90

* 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 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 who report "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 (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. (2025). 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)
	I. Disabled Workers						
	FT + PT	FT incl. Cognitive Disabilities	Work Limiting Disability	Age 18-49	Age 50-64	Men	Women
Change in WFH	0.498**	0.833***	0.729*	0.816***	0.745*	0.585*	0.820**
	(0.245)	(0.276)	(0.397)	(0.305)	(0.436)	(0.307)	(0.395)
First Stage F-Stat	50.72	56.01	45.28	50.95	31.60	67.07	39.33
VtF Confidence Band	[0.034, 0.961]	[0.310, 1.359]	[-0.020, 1.483]	[0.231, 1.393]	[-0.067, 1.633]	[-0.000, 1.171]	[0.078, 1.583]
Occupations	87	87	79	71	80	73	63
	II. Older Workers						
	FT + PT	FT age 50-75	Disabled	Not Disabled	Men	Women	
Change in WFH	0.286***	0.372***	0.378	0.396***	0.368**	0.413**	
	(0.180)	(0.120)	(0.337)	(0.119)	(0.150)	(0.172)	
First Stage F-Stat	80.62	66.91	30.33	75.38	79.73	44.93	
VtF Confidence Band	[0.080, 0.493]	[0.143, 0.602]	[-0.246, 1.050]	[0.168, 0.624]	[0.081, 0.655]	[0.089, 0.736]	
Occupations	90	90	73	90	87	74	

* p<0.1 ** p<0.05 *** p<0.01. Regressions control for labour 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 2 for details of data and estimation.

Table 5: IV effects on other outcomes

	Commute Time	Hours
	(1)	(2)
I. Disabled Workers		
Change in WFH	-2.197***	-0.630***
	(0.296)	(0.179)
Occupations	87	87
II. Older Workers		
Change in WFH	-1.774***	-0.677***
	(0.192)	(0.152)
Occupations	90	90

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Regression includes controls for labour market tightness and are weighted by the inverse of occupation variance. Each column represents a separate sample of older or disabled adults. See table notes for Table 2 for details of data and estimation.

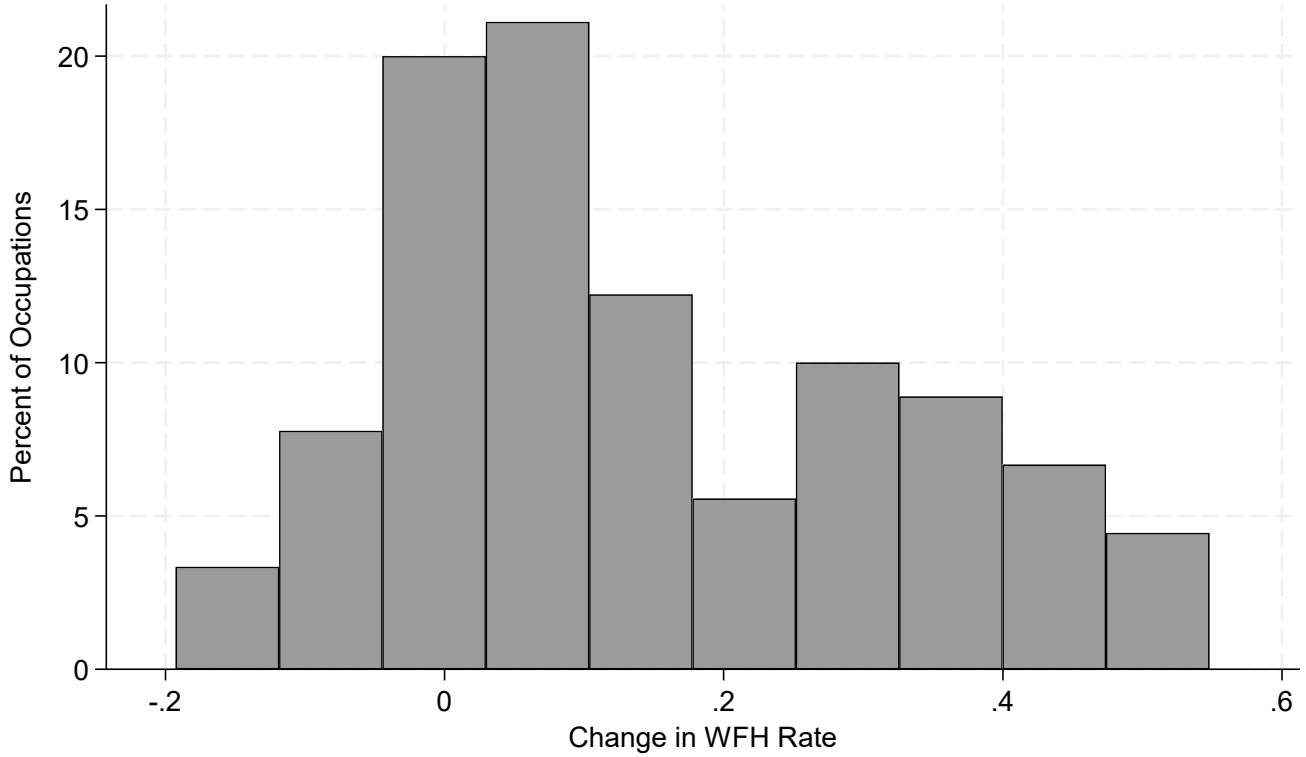
Table 6: Triple interactions on other outcomes

	(1)	(2)
	Hourly Wage	Unemp >1 year
I. Disabled Workers		
Group x Post x High WFH Occ	-0.156	0.042***
	(0.567)	(0.000)
Observations	189,939	13,218
II. Older Workers		
Group x Post x High WFH Occ	-0.210	-0.008**
	(0.831)	(0.000)
Observations	140,680	15,421

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

Appendix: Supplemental Figures and Tables

Figure A1: Distribution of growth in WFH



Notes: Data comes from 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.

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 to 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 Table A3: Robustness check with different labour market controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Disability			Age		
	Panel I. OLS					
Change in WFH	0.446**	0.442**	0.398*	0.292***	0.291***	0.268***
	(0.215)	(0.214)	(0.226)	(0.092)	(0.092)	(0.091)
Non-group employment change (NGEC)	0.926***	1.030**	1.310***	0.370***	0.395***	0.514***
	(0.305)	(0.427)	(0.394)	(0.090)	(0.105)	(0.127)
NGEC^2		0.004	-0.015		0.001	0.003
		(0.011)	(0.011)		(0.002)	(0.002)
NGEC^3			-0.001**			-0.000**
			(0.000)			(0.000)
	Panel II. IV					
Change in WFH	0.785***	0.786***	0.792***	0.358***	0.361***	0.355***
	(0.274)	(0.273)	(0.277)	(0.119)	(0.118)	(0.119)
Non-group employment change	0.665**	0.728*	0.916**	0.324***	0.344***	0.432***
	(0.323)	(0.429)	(0.446)	(0.105)	(0.117)	(0.150)
NGEC^2		0.002	-0.013		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

See Table 2 for notes. Non-group is non-disabled for disability sample and younger for age sample.