

Disability employment and working from home in Australia

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21 August 2026

Abstract

Disability employment rose sharply in Australia after the onset of COVID-19 in 2020. While work from home (WFH) has been proposed as a key mechanism, other explanations include tight labour markets and compositional changes in the disability population. To assess these explanations, the paper combines two empirical approaches: occupation-level instrumental variable analysis, and individual-level difference-in-difference models. The results suggest that expanded WFH access had, at most, a marginal effect on disability employment growth in Australia. Although correlated, increased occupational WFH has no statistically significant causal effect on disability employment once endogeneity controls are included. Instead, disability employment growth is closely linked to broader occupation-level employment growth, consistent with a tight labour market. At the individual level, people with disability had strong post-pandemic employment growth, especially those with more persistent or severe disability or receiving the Disability Support Pension. But these gains were concentrated among individuals in occupations with low pre-pandemic WFH capability, with no effect from occupation-switching after the pandemic. Overall, the findings suggest that full employment, rather than expanded access to WFH, is more important for improving disability employment outcomes, while also highlighting potential roles for institutional settings and social norms.

Keywords: disability employment, work from home, COVID-19 pandemic

JEL Classification: I12, J14, J21, J22

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1 Introduction

Living with disability has long been associated with lower rates of employment and workforce participation in Australia (Ye et al., 2026). Working-age people (15-64 years) with disability had an employment rate of just 47.5% in 2018, compared to 80.3% for their peers without disability (ABS, 2019). The lower rate of labour force engagement has been highly persistent over time – since at least 1993 (ABS, 2015) – and several Australian studies have found these negative employment effects are causally linked to disability onset (Jones et al., 2018; Lane & Liu, 2024; Polidano & Vu, 2015).

Despite this history, the disability employment rate rose sharply after the COVID-19 pandemic began in 2020. In Australia, it increased by nearly 9 percentage points (ppts) to 56.0% in 2022, compared to an increase of just 2ppts to 82.3% for people without disability (ABS, 2024). A similar pandemic trend was evident in the US, where employment among the working-age population with disability (18-64 years) increased by over 12% between the start of the pandemic and 2024, and by over 20% by February 2026 (Bloom et al., 2026).

In the US, there is limited consensus about what is causing the recent rise in disability employment. In Australia, the same trend has not been subject to much examination. Several US scholars have linked the increase to the normalisation of work from home (WFH) arrangements across the US labour force during the pandemic, reducing barriers and improving access to employment for workers with disability (Ne’eman & Maestas, 2023; Schur et al., 2020). The most prominent of these papers, by Bloom, Dahl & Rooth (2026), found that a 1ppt increase in WFH rates in an occupation led to a 1.3% increase in full-time employment for people with disability between 2018-19 and 2022-24 under their instrumented model.

However, other explanations for the rapid increase in disability employment are available. Both the US and Australia had unusual macroeconomic conditions over the same period, with exceptionally tight labour markets that drove strong employment growth for people with disability in both teleworkable *and* non-teleworkable roles (Ameri et al., 2023; Ne’eman & Maestas, 2023). Alternatively, Bartalotti, Dieterle & Kreider (2024) argued that most of the rise in US disability employment is due to compositional shifts in disability, with rising shares of respondents reporting disability after March 2020 (especially cognitive/mental health difficulties) and these newer cohorts more likely to be employed. Within Australia, rollout of the National Disability Insurance Scheme (NDIS) continued over the same period, seeking to improve social, functional and economic outcomes for people with disability (Ranjan, 2025).

This paper asks what explains the post-pandemic increase in disability employment in Australia, and whether expanded access to WFH played a meaningful role. To examine this question, it first replicates the instrumental variable analysis of Bloom, Dahl & Rooth (2026) in Australia, using cross-sectional data from the Australian Bureau of Statistics (ABS, 2024), with extensions to account for uniquely Australian factors. It then exploits the long panel dimension of the Household, Income and Labour Dynamics in Australia (HILDA) survey to estimate difference-in-difference (DiD) models of post-pandemic employment trajectories and test whether relative

employment gains for people with disability were concentrated in occupations that were more WFH-capable prior to the pandemic.

The paper’s main contribution is to examine these questions in the Australian context, as previous research has focused on the US. It finds different results from the US, showing that, despite its potential benefits for people with disability, WFH has not been a major driver of the increase in disability employment in Australia. Specifically, the IV approach finds that increased WFH in an occupation has no statistically significant causal impact on disability employment, once all controls for endogeneity are included. Instead, much of the occupation-level change appears to have been driven by a tight labour market, through a strong relationship between disability employment and non-disability employment. The DiD approach provides evidence that employment grew more strongly after the pandemic for people with disability than for those who never reported disability. However, these increases in relative employment were concentrated among occupations with low pre-pandemic WFH capability, and this pattern is not primarily driven by movements into more teleworkable jobs after the pandemic began. Additional heterogeneity tests also suggest that the strongest employment gains were concentrated among people with more severe work-limiting disabilities and among Disability Support Pension recipients. Taken together, the findings do not support the view that improved access to WFH was the main driver of rising disability employment and are more consistent with a broader labour-market-tightness explanation.

The paper is structured as follows. Section 2 provides an overview of the existing literature on the links between disability and employment, including barriers to employment and the impact of WFH and other factors. Section 3 outlines the data sources used, while Section 4 details the main empirical strategies deployed for each data source. Section 5 contains the main results, starting with descriptive statistics, before moving onto the IV analysis using SDAC and then the DiD analysis using HILDA. Section 6 outlines the heterogeneity and sensitivity analysis used to further explain and reinforce the main results, and Section 7 concludes with a discussion of implications and opportunities for further research.

2 Related literature

The historic gap in employment rates between people with and without disability is typically attributed to significant barriers to work. Depending on the nature of the individual’s disability and occupation, these barriers can include physical, architectural and environmental constraints imposed by structured office work, as well as technological and organisational barriers, such as inaccessible systems, poor communication methods or a lack of support for adjustments, all of which can make employment more costly for many people with disability (Disability Royal Commission, 2023; Igeltjörn & Habib, 2020; Lawrence et al., 2025; Schur et al., 2017). Structural barriers can also contribute to the disability employment gap, such as through complex and poor-quality employment services in Australia (Disability Royal Commission, 2023; Lawrence et al., 2025), or the potential disincentive effects of disability income payments (Autor et al., 2019; Autor & Duggan, 2006; French & Song, 2014).

Attitudinal barriers are an additional factor contributing to the disability employment gap, including potentially discriminatory beliefs and practices from employers, colleagues and customers. There is a large literature examining the persistence and impact of employer stigma about people with disability (Bonaccio et al., 2020; Disability Royal Commission, 2023; Kruse et al., 2018; Lawrence et al., 2025; McFarlin et al., 1991; Ren et al., 2008; Schur et al., 2017).² People with disability can also face resentment (or anticipated resentment) from their colleagues, particularly if they receive adjustments desired by their coworkers (Bonaccio et al., 2020; Colella, 2001; Colella et al., 2004; Kanter, 2022).

Working from home – rather than commuting to an office or workplace – can help workers with disability to overcome many of these employment barriers. Specifically, remote work removes the burdens of commuting with disability, especially on public transport. WFH provides more autonomy and control over the working environment, permitting workers to remain close to medical equipment or to create a more productive workspace through fewer distractions or reduced exposure to stressors. And remote work allows more flexible working schedules, permitting workers who have recurring medical appointments or unpredictable chronic conditions to better optimise their effort over time (Ameri et al., 2023; Brooks & von Schrader, 2023; Das et al., 2021; Hoque & Bacon, 2022; Igeltjörn & Habib, 2020; Kanter, 2022; Schur et al., 2020).³ In addition, workers with disability receive many of the same benefits from WFH as do workers without a disability, including improved job and life satisfaction (Beauregard et al., 2019; Bloom et al., 2015; Rodgers et al., 2025), and reduced work-family conflict (Gajendran & Harrison, 2007; Laß & Wooden, 2023, 2025b).

On the employer side, the pandemic resulted in more managers developing the necessary skills and practices to work with remote employees, while firms and employees made significant investments in capital equipment and new systems during the pandemic to support WFH (Barrero et al., 2021), reducing both the stigma and cost associated with using remote work as an adjustment to support workers with disability (Hoque & Bacon, 2022; Kanter, 2022; Ne’eman & Maestas, 2023). Beyond the strong evidence that employers benefit from WFH through reduced staff turnover and lower absenteeism (Bloom et al., 2015, 2024; Gajendran & Harrison, 2007), analysis of US healthcare workers found WFH arrangements especially important for the retention of employees with disabilities, as not working from home is strongly linked to greater turnover

² Correspondence field experiments using job application callbacks have demonstrated strong evidence of hiring discrimination among employers in the US (Ameri et al., 2018; Hipes et al., 2016) and Europe (Baert, 2016; Ravaud et al., 1992). Meta-analysis of these correspondence experiments finds that people with disability are 41% less likely to receive a callback on average – a larger effect than for discrimination on the basis of ethnicity, gender, sexuality, religion or age (Lippens et al., 2023).

³ For instance, US time-diaries indicate people with a physical or mobility-based disability can face increased costs of switching between activities throughout a day (such as difficulties with transportation or getting dressed) and increased time needed to do some activities (Hamermesh & Myck, 2025), which WFH assists with by reducing activity switching and allowing a more optimal allocation of time across tasks.

intentions (Rodgers et al., 2025).⁴ In addition, greater access to job flexibility among *all* employees can limit the salience of using remote work as an accommodation, reducing discrimination or resentment from coworkers as well (Colella, 2001; Colella et al., 2004).

However, WFH arrangements can have downsides too. Population-wide analysis has found that WFH can increase social isolation, lead to longer working hours or burnout, and result in the blurring of boundaries between work and home (Beauregard et al., 2019; Gajendran et al., 2024; Mas & Pallais, 2020). All these factors can have potentially compounding impacts on people with existing disabilities (Das et al., 2021; Hoque & Bacon, 2022; Pollak et al., 2023). Some evidence also suggests that remote work results in professional isolation, by narrowing professional networks and decreasing skills development through more limited channels of communication, as well as constraining career growth through presenteeism bias (Emanuel et al., 2023; Emanuel & Harrington, 2024; Yang et al., 2022). While surveys of self-reported productivity suggest most people feel they are just as or more productive at home – including workers with disability (Unison, 2020) – the evidence on the productivity impacts of WFH remains equivocal and many employers remain sceptical (Barrero et al., 2023).

In the wake of the pandemic, the population-wide uptake of WFH arrangements has grown rapidly. Prior to the pandemic, about 7% of working days in the US were worked at home (Barrero et al., 2023), while 4.6% of hours were usually worked at home for Australian employees in 2019 (Melbourne Institute & DSS, 2024). As initial pandemic health orders forced people to stay at home, WFH rates spiked – peaking at over 50% of working days in the US in early 2020 (Barrero et al., 2023) and at 23% of hours worked in Australia in 2021 (Melbourne Institute & DSS, 2024) – before declining again and stabilising to a rate of about 27% of working days in the US by July 2025 (Barrero et al., 2025) and about 15% of hours worked in Australia by 2023 (Melbourne Institute & DSS, 2024).

Despite the growth in WFH and its benefits for people with disability, many are in occupations that are difficult to do from home, such as low-wage service or blue-collar jobs. Once these and other differences are accounted for, Australian analysis finds that people with a work-limiting health condition or disability are no more or less likely to undertake at least one day of WFH per week after the pandemic (Laß & Wooden, 2025a). By contrast, similar conditional analysis from the US found that workers with disability were more likely to primarily WFH and to do any WFH before the pandemic (Schur et al., 2020), and remained more likely to WFH from 2020 to 2022 (Ameri et al., 2023).

Comparing Current Population Survey (CPS) data between the pre-pandemic period of January 2018 to December 2019 and the post-pandemic period of July 2022 to June 2024, Bloom, Dahl

⁴ The same analysis also found that WFH does not have any statistically significant impact on job satisfaction for healthcare workers with a disability – beyond a baseline increase in satisfaction for everyone who works remotely – but that having a disability (weakly) attenuates some the positive effects of WFH on job autonomy, perceived organisational commitment and support, employer openness to difference and employer inclusivity (Rodgers et al., 2025).

& Rooth (2026) link the rising rate of WFH to the rise in employment for people with disability in the US. They find that 68–85% of the increase in full-time disability employment was explained by increased WFH, and that a 1ppt increase in WFH in an occupation increases full-time disability employment by about 1.3% in an instrumented model. Given the constraints of the cross-sectional data available, Bloom, Dahl & Rooth (2026) limit their analysis to physical disabilities only – which had relatively similar population sizes pre- and post-COVID – to partly address concerns about compositional shifts in the disability population, due to large increases in the population with cognitive disabilities during the pandemic.

Other scholars have found that, although WFH adoption was an important driver of growing disability employment, tight labour markets mean that growth was much more widespread than just in teleworkable roles. Ameri et al. (2023) used the same CPS data to exploit variation between US states between May 2020 and April 2022 to find that a 1ppt decline in state unemployment rates (tightening a state’s labour market) led to a 2.0% (0.59ppt) increase over the baseline employment rate for people with disability during the pandemic, compared to a 1.2% (0.91ppt) increase in employment for people without a disability.⁵ Similarly, although Ne’eman & Maestas (2023) concluded that the increased disability employment rate from late 2021 was concentrated in teleworkable roles in the US (growing 18.9% faster for people with disabilities by 2022 than for everyone else), the authors also found that disability employment in non-teleworkable roles grew 7.4% faster as well.

To examine the impact of compositional effects, Bartalotti, Dieterle & Kreider (2024) exploit the panel structures of the Survey of Income and Program Participation (SIPP, which follows respondents over a four-year period) to conclude that a higher share of individuals reported having disability after March 2020. These new respondents with disability were more likely to both report cognitive or mental health issues and to have strong existing attachments to the labour force in the years before COVID. Although respondents reporting disability after March 2020 were more likely to be working at home at least some days a week, the authors find that the share of workers with disability in roles amenable to telework declined during the pandemic (–3.3ppt), compared to a rising share for everyone else (+1.2ppt).

Unlike in the US, Australia has also had a significant shift in publicly-funded support for people with disabilities over the same period, through the rollout of the National Disability Insurance Scheme (NDIS) since 2016. Emerging evidence indicates that access to the scheme materially improves labour force outcomes for those not already employed (Ranjan, 2025), potentially providing a different explanation for Australian disability employment growth.

⁵ Although just over half this disability increase came from teleworkable roles (51.8%, compared to 30.5% for people with no disability), the relative growth rate of employment in non-teleworkable roles was still higher for people with disability (0.9% or 0.28ppt) than for people with no disability (0.8% or 0.62ppt) (Ameri et al., 2023).

The present study builds on this rapidly expanding literature by replicating and extending the key analysis in Bloom, Dahl & Rooth (2026), to consider whether and how the employment experience of Australians with disability differs from their US counterparts.

3 Data sources

3.1 Survey of Disability, Ageing and Carers (SDAC)

The first data source for analysis is SDAC, periodically produced by the ABS (2019, 2024). The main analysis uses microdata from the two most recent waves of the SDAC: the 2018 survey (ninth wave, collected between July 2018 and March 2019); and the 2022 survey (tenth wave, collected between June 2022 and February 2023). The 2018 survey sampled 65,805 Australians across households and caring accommodation, while the 2022 survey sampled 43,026 Australians, with individual observations weighted to population-level estimates through weights provided by the ABS. This paper’s estimation approach focuses on employed working-age (15-64 years) Australians, reducing the total sample size to 25,957 in 2018 and 16,638 in 2022.

SDAC’s definition of disability aligns with the International Classification of Functioning, Disability and Health (ICF) – a person is defined as having a disability if they report they have ‘a limitation, restriction or impairment, which has lasted, or is likely to last, for at least six months and restricts everyday activities’. Disabilities are grouped into 6 categories: sensory and speech; learning and understanding; physical; psychosocial; head injury, stroke or acquired brain injury; and/or ‘other’ disabilities.⁶

The SDAC survey waves in 2018 and 2022 asked respondents whether they ‘usually work most hours at home’ in their main job, ‘usually work most hours away from home’ or ‘do not usually work any hours at home’. The structure of the question implies that the population with *any* usual hours of WFH is the sum of those who selected either of the first two answers (or the total employed population less the respondents that answered ‘do not usually work any hours at home’). Alongside these key variables, SDAC 2018 and 2022 also collect data on a respondent’s age, employment status (including full-time and part-time status), highest level of education attainment, occupation by 6-digit Australian and New Zealand Standard Classification of Occupations (ANZSCO) code, industry by 3-digit Australian and New Zealand Standard Industrial Classification (ANZSIC) code, and whether the respondent is receiving an agreed package of support through the NDIS.

3.2 Household, Income and Labour Dynamics in Australia (HILDA) survey

The second data source for analysis is the longitudinal Household, Income and Labour Dynamics in Australia (HILDA) Survey (Melbourne Institute & DSS, 2024). The annual survey has been

⁶ ‘Psychosocial’ disabilities include mental illness and nervous/emotional disorders; ‘physical’ disabilities include blackouts, limitations of the arm, leg or grip, disfigurements, chronic pain, and shortness of breath.

run since 2001 and collects interview responses across a wide range of economic and social questions from approximately 16,000 people in the 9,000 households each year (as of wave 23). As the surveys are typically completed in the second half of the corresponding year⁷ the outbreak of the COVID-19 pandemic in early 2020 occurred between waves 19 and 20, providing a clean cutoff for the start of the pandemic. This paper’s estimation approach focuses on the working-age population (15 to 64 years).

Within HILDA, disability is a self-identified functional condition, with respondents asked whether they have ‘any long-term health condition, impairment or disability that restricts you in your everyday activities, and has lasted or is likely to last, for 6 months or more’ (the *helth* variable). Disability types are self-classified across 18 different conditions that broadly align with ICF classifications, with respondents able to select multiple conditions. There are also further question on whether the condition limits the respondent’s ability to work and a scale of 0-10 to rate that limitation. Through the household survey, HILDA identifies whether individuals have ‘received an agreed package of support’ through the NDIS during the prior 12 months (*hgndi*). However, the question was only included from wave 17 (2017) onwards, in line with the start of the main NDIS rollout, meaning analysis accounting for NDIS support is limited to wave 17 onward.⁸

Alongside responses on employment status (*esdtl*), the HILDA survey collects answers on whether employed individuals undertake any of their ‘usual’ hours of work at home (*jbmh*), including sub-questions about how many hours each week they usually work at home (*jbmhrhw*) or, if hours vary, how many hours they work at home per week on average over a usual 4-week period (*jbmhrha*) and whether this WFH arrangement is a result of a formal agreement with the employer (*jbmagh*). HILDA also asks employed respondents about their occupation (classified by ANZSCO code) and industry (classified by ANZSIC code) of employment.

3.3 Occupational WFH-capability scores

Both empirical strategies make use of the WFH capability (or ‘teleworkability’) scores developed by Dingel and Neiman (2020). These US scores have been cross-walked to 4-digit occupation codes under ANZSCO, using a correspondence matrix from Jobs and Skills Australia (2022). Occupation counts from the 2016 Census (ABS, 2021) were used to aggregate the 4-digit teleworkability scores to the minor (3-digit), sub-major (2-digit) and major (1-digit) classification levels through weighted averages.⁹

⁷ For instance, data collection for wave 23 started in July 2023, with 97.5% of fieldwork completed by December (Summerfield et al., 2024)

⁸ Although access to the NDIS broadly aligns with self-assessed disability status, there are some recipients of NDIS support packages (less than 20 observations each year) who do not have a self-assessed functional disability. This may represent legitimate differences between self-assessment and the eligibility requirements for the NDIS, but may also be measurement error.

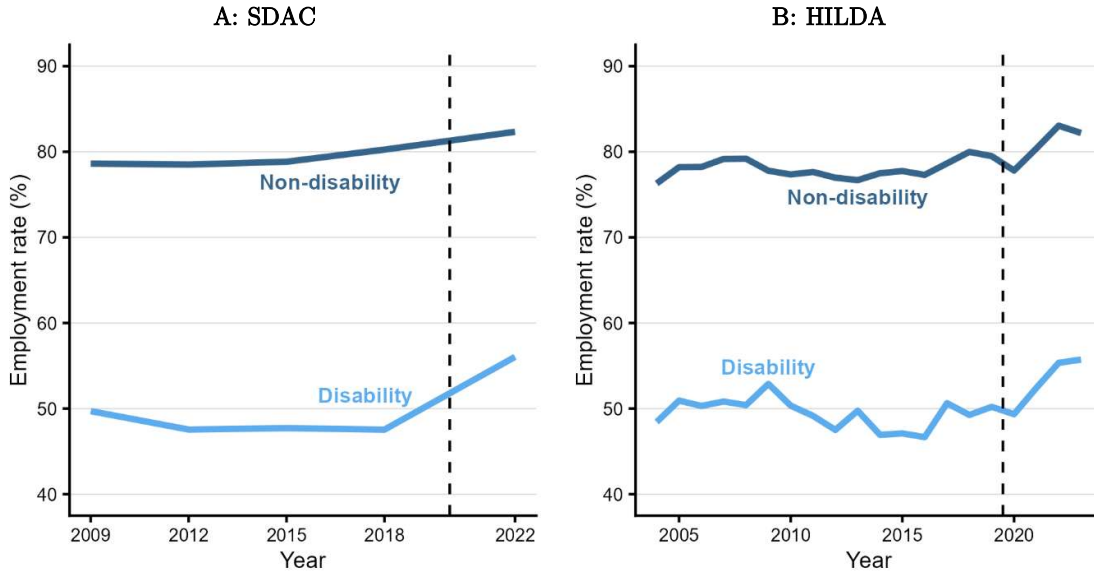
⁹ 2016 Census weights were preferred over 2021 Census weights to avoid distortionary labour market effects of pandemic lockdowns at the time of the 2021 Census on 10 August 2021.

Dingel and Neiman (2020) developed their baseline scores from task-based criteria using O*NET data, but also developed a more flexible set of alternate manually-assigned WFH capability scores that include partial scores of 0.25, 0.5 and 0.75, alongside binary 0 or 1 outcomes. These manually-assigned scores are preferred over the O*NET-based scores, as they broadly align, but where there is deviation between the two scoring systems, judgement suggests the manually-assigned scores are typically superior. For instance, early childhood teachers, child carers, sports-persons and vending machine attendants are all rated as WFH-capable occupations under the O*NET-based methodology, where the manually-assigned scores rate them as unable to WFH, which anecdotal evidence suggests is much more likely.

3.4 Trends in disability employment

Examining time series SDAC data demonstrates that the employment rate for people with disability increased to 56% in 2022, a jump of nearly 9ppt from 2018, and well above its historical bandwidth (Figure 1A). HILDA data shows a similar sharp increase in employment rates in the years after the COVID pandemic (Figure 1B), both for people with disability (by about 7ppts between 2020 and 2023) and for the non-disability population (approximately 5ppts).¹⁰

Figure 1: Employment rates by disability status

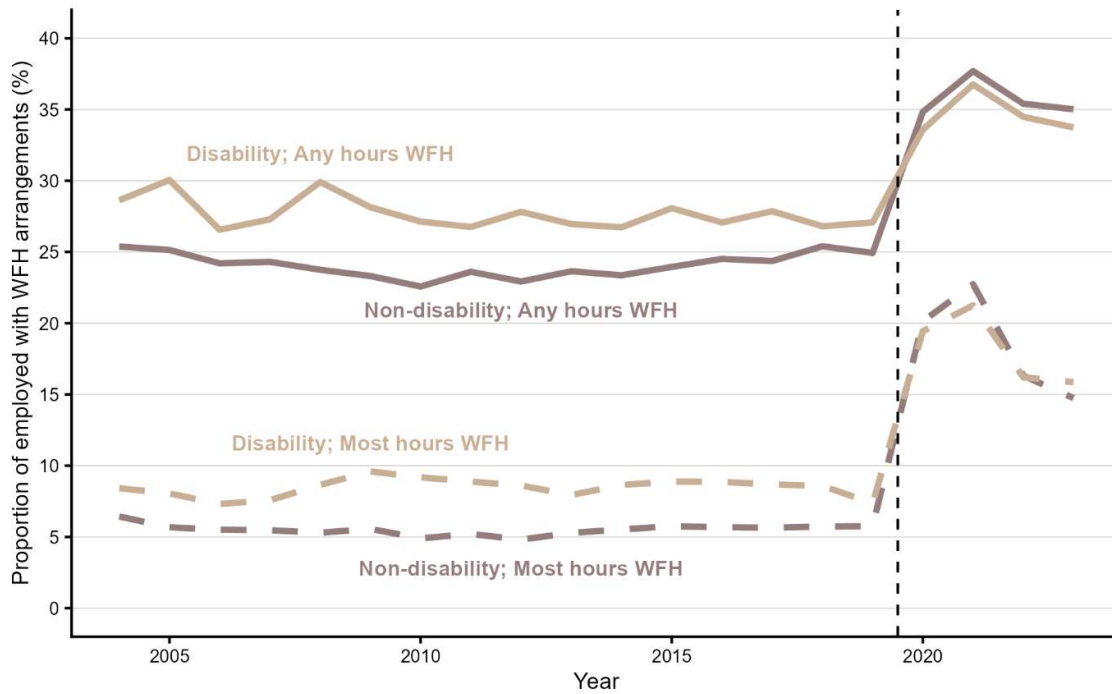


Notes: The left panels depict the population-level estimates of the employment rate ($\frac{\text{working-age employed}}{\text{working-age population}}$) over the five waves of the SDAC between 2009 and 2022, split between populations with and without a disability. The right panel depicts the sample employment rate ($\frac{\text{working-age employed}}{\text{working-age population}}$) from the HILDA survey, split between respondents with and without a disability. Dotted lines denote the start of the COVID-19 pandemic in early 2020. Source: ABS data, accessed through Tablebuilder, and HILDA survey, waves 4 to 23.

¹⁰ Additional disaggregation shows that the largest nominal increase in employment rates occurred for those with a mild-to-moderate work-limiting disability (Figure B.1 in Appendix B).

Despite its potential benefits for people with disability, WFH uptake increased more for non-disability workers during the pandemic. Prior to the pandemic, workers with disability were 6.6ppt more likely to do any WFH hours than their peers without a disability in the SDAC survey (36.8% to 30.2%, respectively), but this gap had narrowed to 3.3ppt in 2022 (42.3% to 39.0%). Within HILDA, there were similar gaps in uptake of any WFH hours and majority WFH hours between people with and without disability, but this had narrowed considerably just before the pandemic (Figure 2). After 2020, remote work shares increased greatly for all groups, but rose much more for workers without a disability, leading to rates of any and majority WFH about 1–2ppt higher.¹¹

Figure 2: WFH rates by disability status

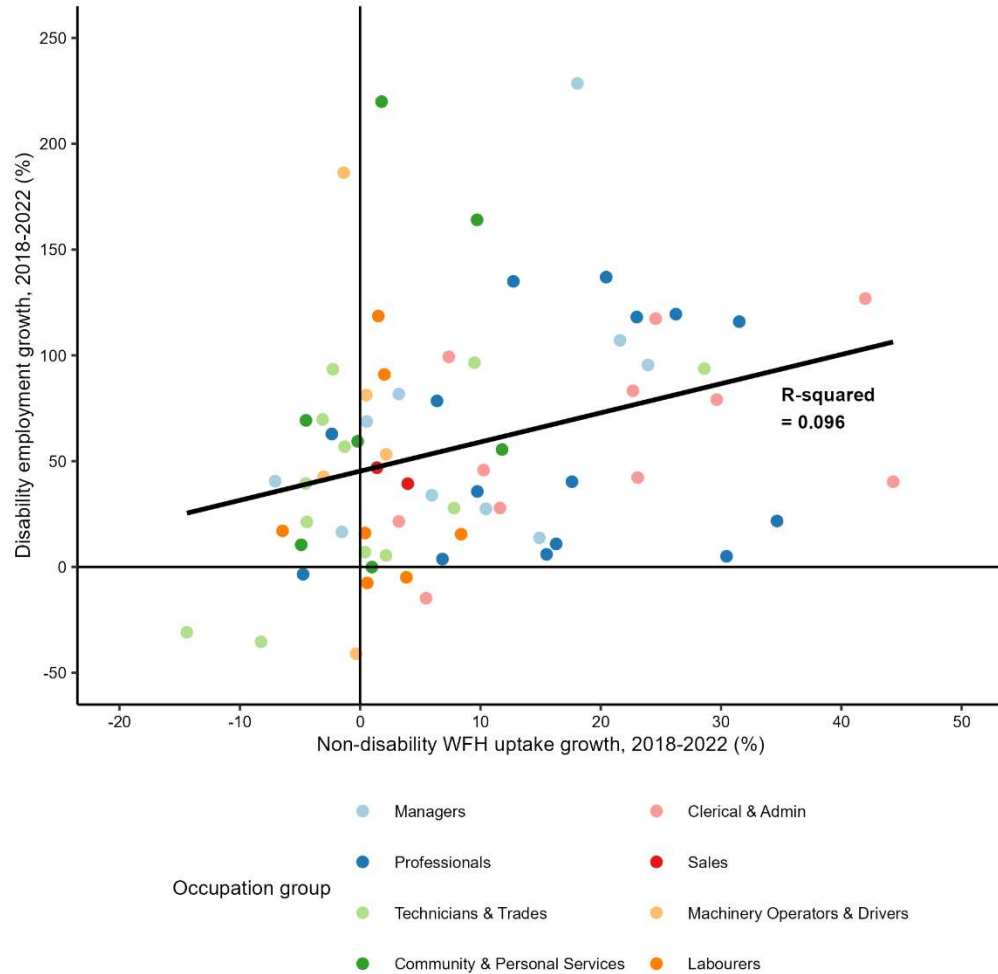


Notes: Chart depicts the proportion of employed working-age individuals in the HILDA sample with any usual hours of WFH each week (solid lines) or with a majority of hours WFH (dashed lines), split between respondents with and without a functional disability in each period, over waves 4 to 23. Dotted line denotes the start of the COVID-19 pandemic between waves 19 and 20. Source: HILDA survey, waves 4 to 23.

¹¹ Different occupation mixes of people with and without disability (often caused by more limited educational opportunities earlier in life or greater rates of work-related disability in specific occupations) lead to consistently lower shares of people with disability employed in WFH-capable occupations (Figure B.2 in Appendix B), despite their greater uptake of WFH arrangements before the pandemic. A strong rise in the share of people with disability in WFH-capable occupations after the pandemic, may be due to greater occupational teleworkability sorting, but may also be explained by compositional shifts.

The SDAC data suggests that there is some weak correlation between the growth in disability employment and the growth in non-disability WFH uptake *within* each 3-digit ANZSCO occupation (Figure 3).¹²

Figure 3: Disability employment growth v WFH growth

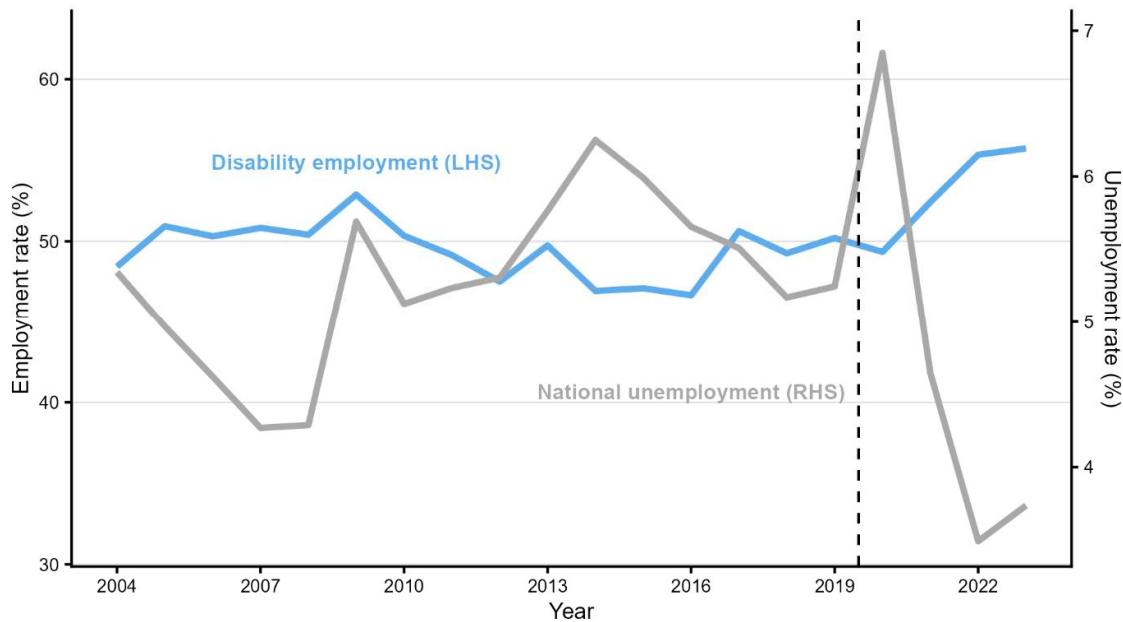


Notes: Chart depicts the relationship between disability employment growth in each occupation between the 2018 and 2022 waves of SDAC, and the change in the proportion of the non-disability population undertaking any WFH in those occupations between 2018 and 2022. Only occupations with 10 or more disability observations are included, for data confidentiality reasons. Source: ABS (2019, 2024).

¹² The relationship between non-disability employment growth and the expansion of WFH in each occupation is much weaker (Figure A.1 in Appendix A).

Comparing the increase in disability employment in HILDA to a common metric for tight labour markets – the national unemployment rate – suggests a weakly inverse relationship between the two (Figure 4), providing support to the argument that rising disability employment may have been due to macroeconomic factors. During periods when the unemployment rate fell (2007–08 and 2021–23), disability employment reached relative peaks (with some lag), although the effects seem to fade once the unemployment rate rises above 5%.

Figure 4: Disability employment and unemployment

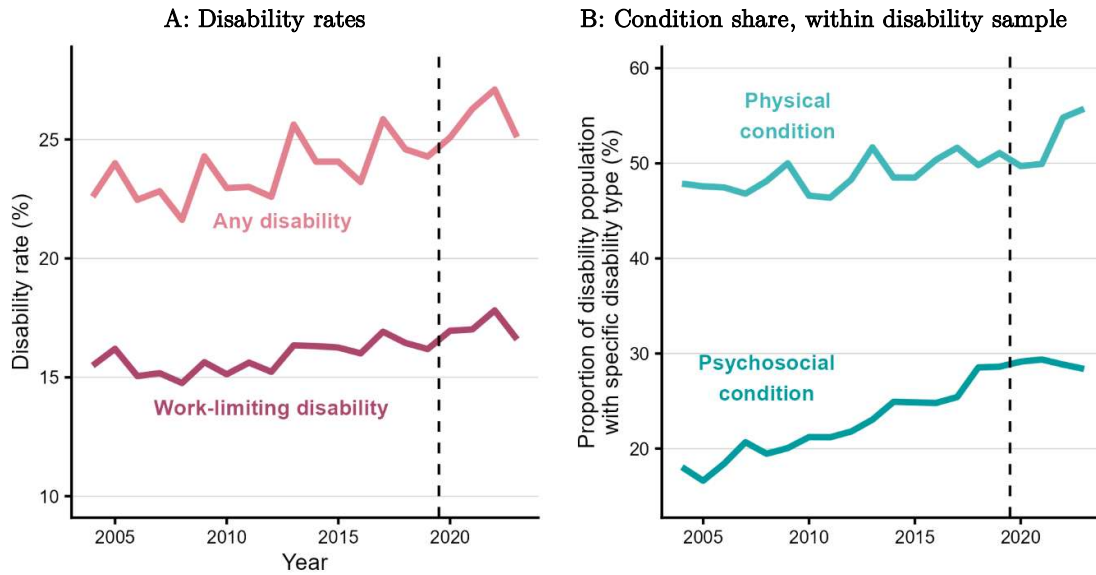


Notes: Chart depicts the employment rate ($\frac{\text{working-age employed}}{\text{working-age population}}$) over 20 waves (2004–2023) for the HILDA sample with a disclosed functional disability (left-hand axis), and the national trend unemployment rate in September each year (right-hand axis). Dotted line denotes the start of the COVID-19 pandemic between waves 19 and 20. Source: ABS Labour Force Statistics and HILDA survey, waves 4 to 23.

There have been considerable changes in the composition of people with disability, including growth in the share of the working-age population reporting a disability over time, up from 13% in 2018 to 16% in the 2022 SDAC survey. The share of working-age respondents with disability in the HILDA survey also increased by several percentage points from 2004 to 2023 (Figure 5A), with about 60% of this cohort then specifying that their disability is work-limiting.¹³ There was also strong growth in the share of people with disability who have a psychosocial condition – up about 5.0ppts between 2018 and 2022 in SDAC, to over 36% of working-age people with disability. Within HILDA, there was a similarly steady increase between 2004 and 2023 in the proportion of people with disability who have a psychosocial condition, compared to a relatively steady share with physical disability (Figure 5B).

¹³ The difference between the rates of disability in HILDA (25.3% in 2022) and SDAC (16.1% in 2022) are likely due to sampling differences and the former’s more expansive survey question, which includes long-term health conditions (ABS, 2019, 2024).

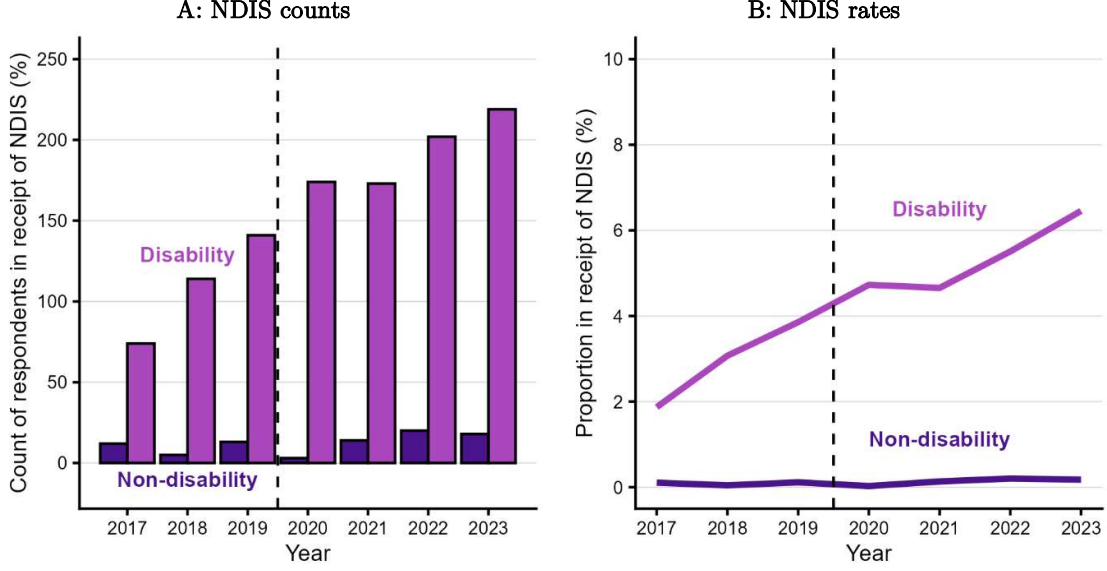
Figure 5: Disability rates and conditions over time



Notes: Panel A depicts the share of working-age respondents reporting a functional disability ('Any disability') and the subset reporting a disability that limits the type or amount of work they can do ('Work-limiting disability'). Panel B depicts the share of the working-age disability sample in HILDA with a psychosocial or physical condition. 'Psychosocial' disabilities include mental illness and nervous/emotional disorders, 'physical' disabilities include blackouts, limitations of the arm, leg or grip, disfigurements, chronic pain, and shortness of breath. Disability conditions are not mutually exclusive. Dotted lines denote the start of the COVID-19 pandemic between waves 19 and 20. Source: HILDA survey, waves 4 to 23.

The expansion of the NDIS is evident in the SDAC survey, with 9% of working-age people with disability receiving an agreed package of support through the NDIS in 2022, up from just over 5% in 2018, providing another potential avenue of support for people with disability seeking employment. There was also considerable growth in the count (Figure 6A) and share (Figure 6B) of NDIS recipients in HILDA between 2017 and 2023, with over 6% of people with disability accessing the NDIS in wave 23.

Figure 6: NDIS recipient rates and counts, by disability status



Note: Charts depict a) the count of responding persons aged 15 to 64 in HILDA who received a NDIS support package in the previous 12 months; and b) the proportion of observations in each group in HILDA that received a NDIS support package in the previous 12 months. Both charts are split between those with a self-assessed functional disability or not ('non-disability'). Dotted line denotes the start of the COVID-19 pandemic between waves 19 and 20. Source: HILDA survey, waves 4 to 23.

4 Occupation-level instrumental variable approach

4.1 Occupation-level empirical strategy

The analysis starts by using SDAC data to regress the change in employment for people with disability on the change in WFH opportunities at the occupation level, similar to the model in Bloom, Dahl & Rooth (2026):

$$\% \Delta \text{employ}_j^d = \beta_1 \cdot \Delta \text{WFH}_j^n + \beta_2 \cdot f(\% \Delta \text{employ}_j^n) + \varepsilon_j \quad (1)$$

In this specification, $\% \Delta \text{employ}_j^d$ is the percentage change in the number of people with disability (superscript d) employed in occupation j between the population-weighted estimates of the 2018 and 2022 SDAC waves. ΔWFH_j^n is the change between the two periods in the percent of workers without a disclosed disability (superscript n) in occupation j who undertake WFH.¹⁴ Using the WFH rate of non-disability workers as the key explanatory variable helps to control for potential reverse causality (if workers with disability have high demand for WFH-capable jobs), relying on the identifying assumption that the rise in total WFH uptake between 2018 and 2022 is

¹⁴ That is, $\% \Delta \text{employ}_j^d = \frac{[\text{emp}_{j,20}^d - \text{emp}_{j,2018}^d]}{\text{em}_{j,2018}^d}$ and $\Delta \text{WFH}_j^n = \text{WFH}_{j,2022}^n - \text{WFH}_{j,2018}^n$, with $\text{WFH}_{j,t}^n$ equivalent to the share of workers without a disability who work at least some hours at home in each occupation. An alternate measure of majority hours at home is examined in robustness tests.

primarily driven by non-disability workers, as people with disability only make up a small share of the employed workforce – approximately 8.0% in 2018 and 11.6% in 2022. The variable of interest is β_1 , which captures the degree to which growth in disability employment in an occupation is driven by growth in non-disability WFH uptake between 2018 and 2022. Growth in non-disability employment by occupation is included through $f(\% \Delta \text{employ}_j^n)$, functioning as a control for common occupation shocks and macroeconomic labour market effects. This control assumes that occupations with high labour demand draw in workers both with and without disability, while the third-order polynomial $f(\cdot)$ accounts for any non-linear relationship. Occupations are aggregated to ANZSCO 3-digit levels, leading to 109 occupation-level cells. To ensure adequate counts for analysis, occupations with less than 5 observations with a disability in either the 2018 or 2022 waves are dropped, reducing the final observation count to around 90 occupations for the main analysis.

To control for observable compositional changes between periods, Bloom, Dahl & Rooth (2026) use an inverse propensity score weighting method to reweight the second period observations based on the observable characteristics in the first period. Employing a similar method – based on Lemieux (2006) – this study uses a logit model to regress the probability that an observation will be in the pre-period on a fully-interacted model of age (5 categories of 10-year bins), gender (2 categories) and education (3 categories for high school, vocational or university). To account for Australia’s unique context, the model also includes interactions with NDIS support (2 categories) – intuitively, this puts less weight on 2022 observations that are receiving NDIS support, given the program’s much earlier phase of rollout in 2018. The inverse-odds using the predicted outcomes from the logit model (P_i) are then combined with ABS-provided population-weights in the SDAC data (ω_{it}) to reweight each 2022 observation so that the distribution based on observables is the same as in 2018.¹⁵

Despite these controls, some reverse causality may still remain, particularly if occupations experiencing increased disability employment also endogenously expanded access to WFH for all employees to accommodate their changing workforce composition, which would overstate the effect of WFH on disability employment. In addition, unobserved occupation-specific labour-demand shocks during the pandemic (such as variations in occupation labour market tightness, or differential exposure to pandemic health order or task-based disruptions) may affect disability employment growth differently to non-disability employment growth. Controlling for non-disability employment growth helps to absorb common occupation-level shocks, but is an imperfect proxy for labour market tightness and does not fully capture shocks that differentially affect workers with disability within occupations.

¹⁵ Specifically, this results in new sample weights in the post-period: $\omega_{i,2022}^* = \frac{P_i}{1-P_i} \omega_{i,2022}$.

To address the remaining endogeneity, the analysis uses an instrumental variable (IV) strategy, exploiting the occupation WFH-capability scores from Dingel-Neiman (DN_j) as an instrument for actual WFH rates in each occupation. The first-stage equation for this approach is:

$$\Delta WFH_j^n = \lambda_1 \cdot DN_j + \lambda_2 \cdot f(\% \Delta employ_j^n) + \mu_j \quad (2)$$

Consistent with Bloom, Dahl & Rooth (2026), this paper finds that the instrument is highly relevant. Its validity relies on the assumption that, conditional on controls, pre-pandemic WFH capability is orthogonal to occupation-level shocks that directly affected disability employment during the pandemic. Although teleworkability is correlated with lockdown edicts and labour-demand shocks in ‘non-essential’ industries, the exclusion restriction requires that WFH capability is not correlated with shocks that had a *differential* impact on disability employment within an occupation, beyond what is captured by the non-disability employment growth variable.

4.2 Instrumental variable results

The main results for the IV strategy are reported in Table 1, where columns 1-4 report regression outputs in a simple OLS framework, while columns 5-8 report the results under the IV approach, with column 8 reflecting the main specification with all controls.

Although the estimates from the full OLS specification suggests that a 1ppt rise in WFH uptake within an occupation is correlated with a 1.3ppt rise in disability employment, the estimate is substantially attenuated under the IV approach, as the associated change in disability employment falls to 0.58ppts in the main IV specification, which is statistically indistinguishable from zero. Given the causal identification strategy employed, the IV results provide substantial evidence that the increase in WFH uptake was not the primary driver of rising disability employment after the pandemic.

Instead, the linear labour market controls remain both economically and statistically significant across all specifications, consistent with a tight labour market explanation for disability employment growth, as occupations with fast growing disability employment also had fast growth in non-disability employment. Adding compositional controls only had minor attenuating effects on the specifications, indicating that the compositional shifts that occurred between 2018 and 2022 may be slightly correlated with increased WFH, but only very weakly.¹⁶

The first-stage results confirm that the instrument is strong, with a highly significant coefficient and an F-statistic above 52 under all specifications, comfortably exceeding the typical threshold of 10 for determining instrument strength (Staiger & Stock, 1997).

¹⁶ In particular, women, middle-aged people, and university graduates are all more likely to WFH (Barrero et al., 2023; Buckman et al., 2025), and experienced growth in their share of the sample between 2018 and 2022 (Table A.1 in Appendix A).

Table 1: Occupation-level IV results – Effect of WFH growth on total disability employment

Dependent variable: Change in disability employment ($\% \Delta \text{employ}_j^d$)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in WFH (ΔWFH_j^n)	1.422** (0.517)	1.147* (0.475)	1.337** (0.493)	1.331** (0.453)	0.817 (0.959)	0.132 (0.940)	0.668 (0.962)	0.583 (0.924)
Labour market controls (change in non-disability employment):								
$\% \Delta \text{employ}_j^n$		205.603*** (47.749)		163.951** (52.373)		223.130*** (52.134)		166.146** (51.200)
$(\% \Delta \text{employ}_j^n)^2$		-63.68 (41.792)		-50.862 (44.346)		-62.48 (42.545)		-46.899 (40.852)
$(\% \Delta \text{employ}_j^n)^3$		-35.65 (58.361)		18.098 (66.791)		-42.678 (59.180)		12.644 (66.597)
First-stage instrument (DN_j)					22.430*** (3.076)	22.295*** (3.422)	22.074*** (3.050)	22.046*** (3.166)
Compositional controls			X	X			X	X
IV approach					X	X	X	X
Occupation cells	89	89	89	89	89	89	89	89
Outcome regression R^2	0.052	0.141	0.046	0.105	0.007	0.108	0.005	0.062
First-stage F-statistic					57.21	52.15	56.05	53.58

Note: The dependent variable is the change in the count of people with a disability employed in an occupation between the 2018 and 2022 SDAC waves, using ABS-provided survey weights. The main independent variable is the change in the share of people without a disability in an occupation who did not report that they ‘do not usually work any hours at home’ in 2022 versus 2018 within the SDAC. Labour market tightness is controlled through a third-order polynomial of the change in non-disability employment. Compositional controls use an inverse propensity score weight based on fully-interacted regression models for age (5 categories), gender (2 categories), education (3 categories) and NDIS status (2 categories). The instrument is the pre-pandemic teleworkability of an occupation, derived from Dingel and Neiman (2020). Occupation is defined using three-digit ANZSIC codes. Heteroskedasticity-robust standard errors are in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Disaggregated estimates show that full-time employment outcomes had a very similar pattern to the baseline total employment model (Panel A of Table A.2 in Appendix A), with significant initial results that are severely attenuated in the IV specifications, no longer suggesting any statistically meaningful relationship between WFH uptake and disability employment. These results differ from the headline full-time employment results from Bloom, Dahl & Rooth (2026), which found that a 1ppt increase in an occupation’s non-disability rates of WFH leads to a 1.1ppt increase in full-time disability employment, which may be due to different institutional settings and social norms between the US and Australia. By contrast, the part-time employment results (Panel B of Table A.2 in Appendix A) suffer from much smaller sample sizes in each occupation, resulting in less precise coefficient estimates that – despite being much larger than the baseline results – are not statistically significant under any specification.

4.3 Heterogeneity and sensitivity analysis

To examine whether the main results are sensitive to disability conditions, Table A.3 in Appendix A constrains the definition of disability within the SDAC sample to people with only a non-psychosocial disability. The results find no change from the main results, suggesting that observed employment growth from WFH is not any more or less concentrated among people with psychosocial conditions.¹⁷

Using an alternate explanatory variable of the non-disability share of an occupation undertaking *majority* WFH hours – instead of the share undertaking *any* WFH hours – finds an attenuation of the main results for the key coefficient of interest (Table A.4 in Appendix A). This suggests that there is no relationship between majority WFH uptake and disability employment growth. However, the strength of the instrument increased in the first stage, indicating the Dingel-Neiman scores are stronger predictors of majority WFH arrangements than of any hours of WFH.

Excluding NDIS support from the compositional controls (Table A.5 in Appendix A) results in estimates that are slightly attenuated across most specifications. This means the inclusion of NDIS support dampens the impact of the compositional controls, indicating that increased NDIS support between 2018 and 2022 is negatively correlated with WFH uptake, potentially because NDIS support is need-based, so may not include many people employed in WFH roles due to other characteristics.

¹⁷ This is roughly equivalent to the main results of Bloom, Dahl & Rooth (2026), which removed all observations with ‘cognitive difficulties’ from the sample to control for compositional changes due to recent rapid growth in those conditions. Working in the other direction, sensitivity testing by Bloom, Dahl & Rooth (2026) found that the *inclusion* of ‘cognitive’ disabilities increased the size and significance of their coefficient estimates. Within SDAC, there are not sufficient observations of people with psychosocial conditions to examine them in isolation.

5 Individual-level difference-in-difference approach

5.1 Individual-level empirical strategy

The second approach is to examine the impact of WFH access on disability employment within the HILDA panel data, exploiting the start of the pandemic in 2020 as a natural experiment that acted as a shock affecting employment outcomes for people both with and without disability, within a difference-in-difference (DiD) design.

The DiD analysis starts with a dynamic two-way fixed effects model to examine post-pandemic employment outcomes for people with disability, which can be expressed as:

$$Y_{it} = \sum_{k \in \mathcal{K}} \lambda_k Disability_i \times 1\{\ell(t) = k\} + X'_{it}\beta + \gamma_i + \delta_t + \varepsilon_{it} \quad (3)$$

where the dependent variable, Y_{it} , measures whether an individual is employed (equivalent to the employment rate), or employed full-time or part-time. Given disability status can vary over time, the treatment indicator $Disability_i$ identifies individuals with a consistent functional disability across all observed pre-pandemic years (2017–2019). Alternate definitions of disability are tested in the sensitivity analysis. The control group consists of individuals who never identified as having a disability during the pre-pandemic period, with respondents dropped if they are not in either group (i.e., they had an inconsistent pattern of pre-pandemic disability identification). Within the specification, $\mathcal{K}$ is a finite series of leads and lags, such that $\mathcal{K} = \{-3, -2, -1, 0, 1, 2, 3\}$ and $\ell(t)$ is an event time measure, counting HILDA waves since the start of the pandemic (wave 20). That is, if t^* represents that start of the pandemic in 2020, then $\ell(t) = t - t^*$ and $\ell = 0$ in 2020. Estimates are normalised to a baseline of zero in 2019 ($\ell = -1$).

The key term of interest is the estimator λ_k , with coefficients for $k < 0$ representing placebo pre-trends, while coefficients for $k > 0$ represent the post-COVID employment dynamics in an event study framework. The estimator relies on the key identifying assumption of parallel trends – that is, absent COVID, the gap in employment outcomes between disability and non-disability cohorts would have remained the same – which is tested through pre-trends analysis. The specification also includes fixed effects at the individual (γ_i) and year (δ_t) level, as well as time-varying controls (X'_{it}) that include the respondent’s age-squared (for non-linear lifecycle effects) and a binary variable for whether the respondent is a recipient of NDIS support, to absorb contemporaneous variation associated with the NDIS (though this can be endogenous and should be treated cautiously).

As a second stage, the model is then expanded into a triple difference (DDD) specification to examine whether employment rose more for people with disability in teleworkable occupations, relative to others, which is expressed as:

$$Y_{it} = \sum_{k \in \mathcal{K}} [\tau_k \text{Disability}_i \times DN_i^{pre} \times 1\{\ell(t) = k\}] + \sum_{k \in \mathcal{K}} [\lambda_k \text{Disability}_i \times 1\{\ell(t) = k\}] + \sum_{k \in \mathcal{K}} [\theta_k DN_i^{pre} \times 1\{\ell(t) = k\}] + X'_{it}\beta_1 + \gamma_i + \delta_t + \varepsilon_{it} \quad (4)$$

where DN_i^{pre} is the teleworkability score of the individual's 4-digit ANZSCO occupation before the pandemic, based on Dingel and Neiman (2020). The main specification uses the modal occupation for the three pre-pandemic years (2017 to 2019) to improve occupational stability. As individuals who are not employed do not have any observed occupation in HILDA, this would ordinarily make pre-pandemic occupational teleworkability contingent on labour force status and preclude identification for non-employed individuals. To adjust for this, the analysis employs a 'last job held' approach to occupations, assuming that non-employed individuals retain the same occupation they were last observed in across the full HILDA sample, in line with similar panel data analysis by Carrillo-Tudela & Visschers (2023) and standard reporting available in US Current Population Survey data (Şahin et al., 2014).¹⁸

The key estimators of interest in the DDD model are the triple interaction coefficients τ_k , which measure the employment effects of having greater access to WFH before the pandemic for people with disability, over and above the lower-order effects for disability status (θ_k) and WFH access (λ_k). The identifying assumption associated with this estimator is that the disability employment gap would have evolved similarly between jobs with high and low WFH-exposure in the absence of the pandemic. In short, if the increase in disability employment was a function of improved WFH access, then employment outcomes for people with disability in occupations with greater access to WFH – such as those in more teleworkable roles pre-pandemic – should be greater than for those in non-teleworkable roles.

5.2 Difference-in-difference results

The results from the two-way disability DiD analysis (Table 2 and Figure 7) confirm that the increase in disability employment observed in the descriptive statistics reflects a genuine post-pandemic improvement, relative to the non-disability group.¹⁹ Total employment rates for people with disability increased by around 3.0ppt after the onset of the pandemic, relative to total employment rates for people without disability, with the effect size rising over time to 5.7ppts by 2023. Most of the increase came from full-time employment, although there is a modest gain in part-time employment in the last year of analysis. The NDIS coefficient is negative, suggesting

¹⁸ The 'last job held' approach assumes that a non-employed individual's occupation does not change until they are employed (i.e. occupations are only carried forward in time, not backward), preventing examination of occupation switchers, who would mechanically have higher employment.

¹⁹ Summary statistics for the main variables of interest are in Table B.1 in Appendix B.

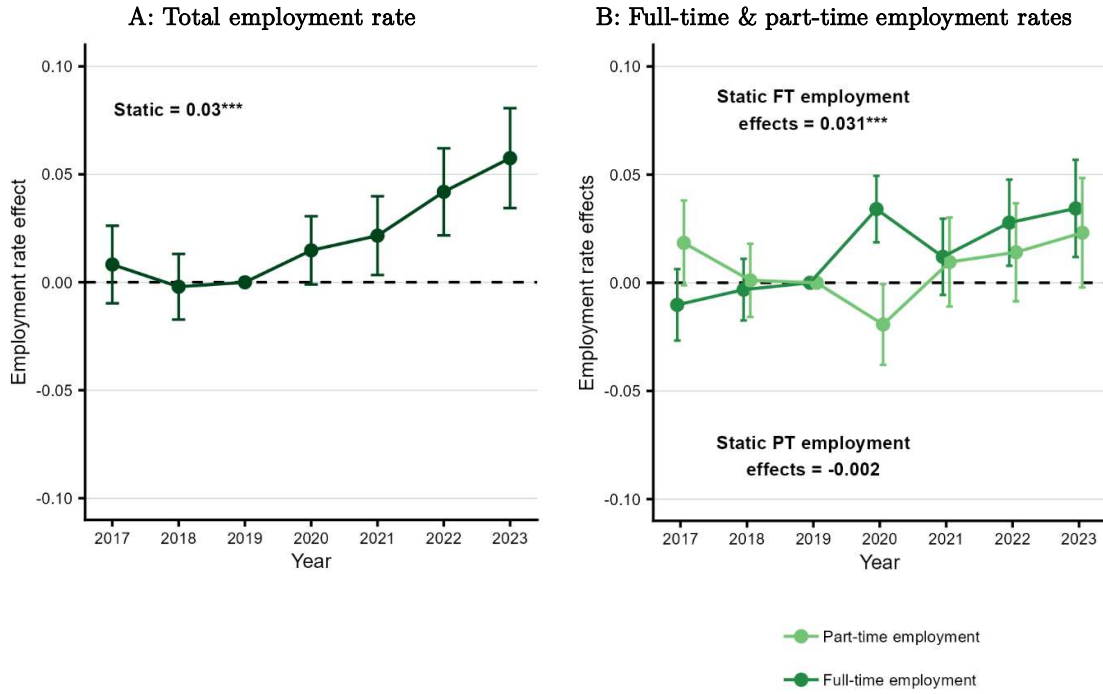
that contemporaneous NDIS support is associated with lower relative employment and full-time employment, consistent with Ranjan (2025).

Table 2: Disability DiD regression results, by employment status

Dependent variable:	(1) Employment rate	(2) Full-time employment rate	(3) Part-time employment rate
Disability			
t = -3 (2017)	0.008 (0.009)	-0.010 (0.008)	0.018+ (0.010)
t = -2 (2018)	-0.002 (0.008)	-0.003 (0.007)	0.001 (0.009)
t = 0 (2020)	0.015+ (0.008)	0.034*** (0.008)	-0.019* (0.010)
t = 1 (2021)	0.022* (0.009)	0.012 (0.009)	0.010 (0.010)
t = 2 (2022)	0.042*** (0.010)	0.028** (0.010)	0.014 (0.012)
t = 3 (2023)	0.057*** (0.012)	0.034** (0.011)	0.023+ (0.013)
<i>Static treatment effect</i>	<i>0.030*** (0.007)</i>	<i>0.031*** (0.007)</i>	<i>-0.002 (0.008)</i>
Age-squared	-0.001*** (0.000)	-0.001*** (0.000)	0.000** (0.000)
NDIS support	-0.035* (0.015)	-0.052*** (0.011)	0.017 (0.014)
Observations	66,506	66,506	66,506
R^2	0.716	0.709	0.548

Note: DiD regression results for the main disability specification. Static (italicised) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include fixed effects at the individual and year level. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 7: Disability DiD event study plots



Note: Event study plots for $Disability_i$ in a two-way DiD specification, split by dependent variables. Effects measured against 2019 pre-treatment baseline, error bars represent 95% confidence intervals, standard errors clustered at individual levels. Data sourced from HILDA, waves 17–23.

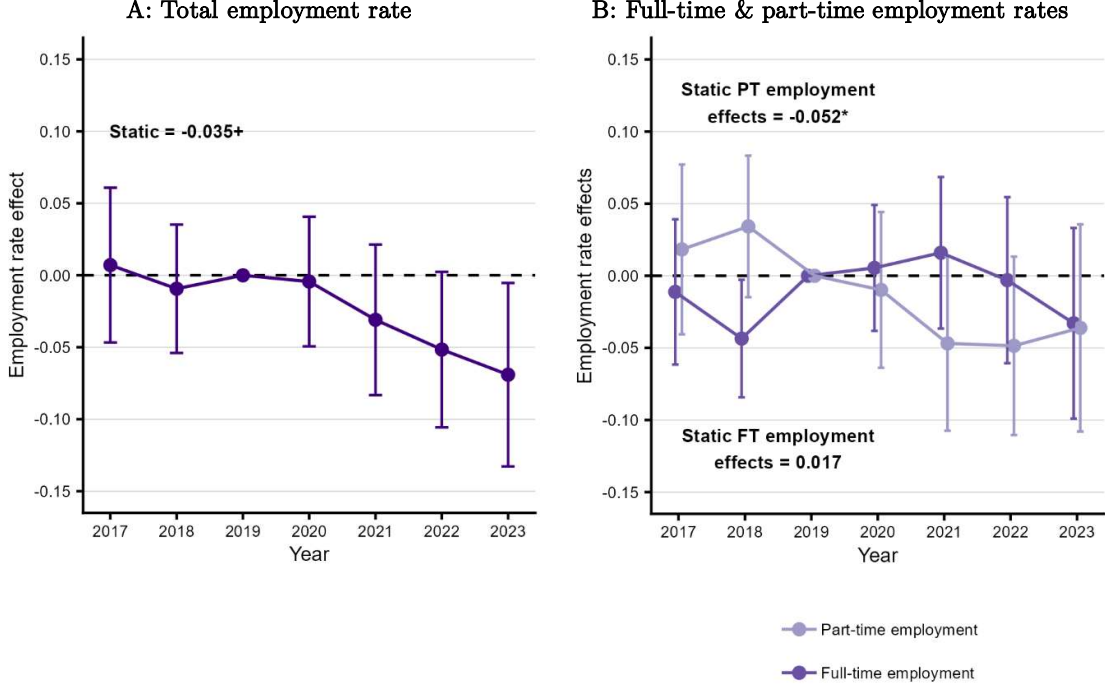
The results for the triple difference analysis, splitting disability employment effects by pre-pandemic WFH-capability (Table 3 and Figure 8), finds that people with disability in WFH-capable occupations prior to the pandemic were *less* likely to be employed after the pandemic, relative to the control group, with this effect accumulating over time, reaching a 6.9ppt decrease by 2023. Lower-order effects for disability only (reflecting individuals with a disability who were in non-teleworkable occupations) are also consistent with the results from the two-way DiD, with statistically significant increases in relative total employment, peaking at a 7.3ppt increase by 2023. As the triple interaction terms and the lower-order disability effects are effectively offsetting, this suggests that disability employment gains were concentrated among workers in occupations with lower pre-pandemic WFH capability, consistent with a labour market tightness explanation for disability employment growth, despite the potential benefits of improved WFH access to people with disability.

Table 3: Triple difference regression results, by employment status

Dependent variable:	(1) Employment rate	(2) Full-time employment rate	(3) Part-time employment rate
Disability x pre-pandemic teleworkability score			
t = -3 (2017)	0.007 (0.027)	-0.011 (0.026)	0.018 (0.030)
t = -2 (2018)	-0.009 (0.023)	-0.044* (0.021)	0.034 (0.025)
t = 0 (2020)	-0.004 (0.023)	0.005 (0.022)	-0.010 (0.028)
t = 1 (2021)	-0.031 (0.027)	0.016 (0.027)	-0.047 (0.031)
t = 2 (2022)	-0.052+ (0.028)	-0.003 (0.029)	-0.049 (0.032)
t = 3 (2023)	-0.069* (0.033)	-0.033 (0.034)	-0.036 (0.037)
<i>Static treatment effect</i>	<i>-0.035+ (0.020)</i>	<i>0.017 (0.020)</i>	<i>-0.052* (0.022)</i>
<i>Disability (static)</i>	<i>0.030** (0.011)</i>	<i>0.020+ (0.011)</i>	<i>0.010 (0.012)</i>
<i>Pre-pandemic teleworkability score (static)</i>	<i>0.015* (0.006)</i>	<i>-0.032*** (0.009)</i>	<i>0.046*** (0.008)</i>
Age-squared	-0.001*** (0.000)	-0.001*** (0.000)	0.000*** (0.000)
NDIS support	-0.045* (0.019)	-0.062*** (0.014)	0.017 (0.019)
Observations	59,757	59,757	59,757
R ²	0.676	0.694	0.555

Note: DDD regression results by dependent variable. Static (*italicised*) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include fixed effects at the individual and year level. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 8: Triple difference event study plots



Note: Event study plots for the triple difference interaction ($Disability_i \times DN_i^{pre}$) in the main DDD specification, split by dependent variables. Effects measured against 2019 pre-treatment baseline, error bars represent 95% confidence intervals, standard errors clustered at individual levels. Data sourced from HILDA, waves 17–23.

Static lower-order effects for the WFH-capability coefficient indicate that, absent disability effects, individuals in occupations with a greater capacity to WFH before the pandemic have 1.5ppt higher employment rates. The net effect on total employment is driven by large positive effects for part-time employment (4.6ppt) and negative effects for full-time employment (−3.2ppts). Detailed analysis in Appendix B (Table B.2 and Figure B.3) shows that the triple difference specification results are replicated in a two-way DiD specification using only WFH-capability (DN_i^{pre}) as the treatment indicator. Underlying trends (Figure B.4 in Appendix B) indicate that the relative results are being driven by strong growth in full-time employment and an associated decline in part-time employment for those in less teleworkable occupations, not by any decrease in employment intensity for individuals in more WFH-capable roles.

5.3 Heterogeneity and sensitivity analysis

Heterogeneity analysis (Table B.3 in Appendix B) finds that most of the aggregate disability employment effects are driven by men, not women, particular for the growth in full-time employment for people with disability in non-teleworkable roles. By age, aggregate employment increases for people with disability were larger for people aged 45 and under, mostly through part-time employment gains, but gains in full-time employment were greater for those aged over 45.

Narrowing the disability definition to people with disability who were also receiving the Disability Support Pension (DSP, around 22% of the total) finds that the post-pandemic employment gains are concentrated in this cohort (Table B.4 in Appendix B), despite DSP recipients facing limits on hours worked and income before payments are reduced or suspended (SCARC, 2022; Services Australia, 2025). The estimated relative employment increase for DSP recipients is 10.0ppts, mostly through full-time employment gains, with gains concentrated among those in non-teleworkable occupations, due to offsetting negative (though often imprecisely estimated) triple-interaction effects.

Table B.5 in Appendix B re-estimates the model using a stricter work-limiting disability definition (based on the *helthwk* variable in HILDA) and presents heterogeneity results that split this group into those with a ‘moderate’ (< 5 on the 0-10 scale in the *helthdg* variable) or ‘severe’ work limitation (≥ 5).²⁰ The results find that post-pandemic employment gains are concentrated among people with a work-limiting disability, with larger coefficients on the lower-order disability effect (5.4ppts), but these gains are again offset by declining relative employment for people with a work-limiting disability in teleworkable occupations before the pandemic. Within the work-limiting disability cohort, positive employment effects are concentrated among those with more severe work limitations, particularly through stronger full-time employment.

Alternate measures of disability persistence are examined in Table B.6 in Appendix B: an ‘ever pre-pandemic’ definition, which classifies individuals as having disability if they reported a disability or long-term health condition in *any* pre-pandemic year; and an ‘always’ definition, which restricts the disability group to individuals who identified as having a disability in every observed year, including the post-pandemic period.²¹ Compared to the main results, both alternate definitions produce attenuated or even null effects, suggesting the main findings are strongest for individuals with more stable pre-pandemic disability status, but that part of the estimated post-pandemic employment effects reflect changes in disability composition over time, including movement into or out of disability identification after the pandemic began.

Static estimations split between overlapping cohorts who never reported specific disability types (Table B.7 in Appendix B) suggest that post-pandemic employment gains are stronger among respondents whose disability profile included a psychosocial condition, particularly for those in low-WFH-capability roles.²² By contrast, weaker relative employment outcomes in more

²⁰ Work-limiting disability definitions may be vulnerable to justification bias, where respondents rationalise non-employment by reporting themselves as unable to work (Bound, 1991).

²¹ As the ‘always’ disability definition conditions treatment status on post-treatment information, it should only be interpreted as a sensitivity test, not an alternate causal specification.

²² Given individuals often have multiple disability types, the robustness checks exclude respondents who ever reported particular disability types: psychosocial disability (a mental illness and/or a nervous or emotional disorder); sensory disability (speech, sight or hearing conditions); and physical disability (black-outs, limitations of the arm, leg or grip, disfigurements, chronic pain, and/or shortness of breath). Overlaps across disability types mean that these results should be interpreted as indicative heterogeneity checks, not definitive estimates of employment effects by mutually exclusive disability type.

teleworkable occupations are more evident among respondents without a history of physical disability, with much of this pattern driven by lower part-time employment.

Among those who are employed, people with disability are much more likely to be self-employed (Figure B.5 in Appendix B), partly due to occupational variation. Table B.8 in Appendix B examines whether the increase in total employment rates for people with disability is related to changes in self-employment, rather than employee outcomes. The results find that the disability employment gains were entirely driven by employees, with no statistically significant change in self-employment outcomes after the pandemic for people with disability, with WFH-capable roles or with both, compared to the control group.

As estimated employment gains among workers in low-WFH-capability roles may reflect some post-pandemic occupational reallocation into more teleworkable jobs, Table B.9 in Appendix B re-estimates the triple-difference model on a restricted sample of individuals with unchanged WFH-capability scores across all periods. The results are similar to the main findings, with static estimates showing an increase in employment for people with disability (4.2ppts), alongside an offsetting reduction in relative employment for the disability cohort in more WFH-capable roles (around 7ppts by 2022 and 2023), indicating that employment growth for people with disability did not come from shifts into more teleworkable occupations after 2020.²³

Re-estimating the triple-difference model on a balanced panel across waves 17 to 23 of HILDA (Table B.10 in Appendix B) finds similar coefficient estimates for the lower-order static effects as in the main findings. The dynamic triple-difference interaction effects are also similar, but are less precisely estimated and hence not individually or jointly significant, potentially reflecting both reduced sample size and the more selective composition of observed individuals in the balanced panel specification.²⁴

6 Discussion and conclusion

In the wake of the pandemic, increased access to WFH was expected to greatly benefit workers who face significant barriers and obstacles to employment, especially people with disability. By providing increased autonomy and flexibility over the working environment, while reducing the costs and inconvenience of transportation, WFH could help to lower barriers to employment. Significant investments by firms in the skills and infrastructure needed to support WFH during

²³ As this sensitivity test conditions sample selection on post-treatment information, it should not be interpreted as a causal specification. Descriptive analysis also finds that changes in occupational teleworkability are rare: by 2023, four-fifths of individuals remain in an occupation with the same pre-pandemic WFH-capability score, while people with disability were less likely to move into more teleworkable roles (Figure B.6 in Appendix B).

²⁴ Although the balanced panel is only modestly smaller than the unbalanced panel (around 7% fewer observations), restricting the sample to individuals observed in every wave can induce non-random selection, particularly as HILDA attrition is correlated with employment status (Summerfield et al., 2024) and health and disability are associated with non-response outcomes (Watson & Wooden, 2009).

the pandemic were also expected to reduce the cost to employers of using WFH as a reasonable accommodation for workers with disability.

Yet, despite its many advantages for people with disability and a rapid rise in disability employment rates after the pandemic, this study finds that increased WFH access has had, at best, a marginal impact on improving disability employment outcomes. At an occupation-level, the causal relationship between increased WFH access and disability employment growth is statistically indistinguishable from zero, despite an apparent correlation between the two variables. The occupation-level estimates instead suggest that most of the increase in disability employment was driven by the macroeconomic effects of tight labour markets, as good employment prospects drew more people with disability into the workforce and encouraged employers to hire them.

Extending the analysis to individual employment trajectories, this paper finds that by 2023, the pandemic had led to stronger employment growth for people with disability than for those who never reported disability. However, these relative employment gains were negligible for people with disability who were in more teleworkable occupations before the pandemic, despite this group having the most to gain from improved WFH access. Disability employment gains were instead concentrated among those in low-WFH-capability occupations, with no evidence of the effects being driven by switching into more teleworkable occupations, consistent with a broader labour-market-tightness explanation for rising disability employment. Sensitivity analyses also indicate that the strongest employment gains were concentrated among people with more severe work-limiting disabilities and DSP recipients, suggesting post-pandemic labour markets may have been especially beneficial for groups facing greater barriers to employment.

Part of the reason for the muted effects of WFH on disability employment growth – and the diverging results compared to similar analysis in the US – may be attributable to Australia’s unique employment settings. Although Australia has similar employer obligations as the US, requiring ‘reasonable accommodations’ or ‘reasonable adjustments’ to support disability employment, the Australian *Fair Work Act 2009 (Cth)* also explicitly entitles employees with a disability to request flexible working arrangements (including WFH arrangements), unlike in the US. Together, these provisions may have allowed many more people with disability in Australia to access WFH arrangements prior to the pandemic, demonstrated by their higher WFH uptake than people without a disclosed disability, despite being less likely to be in WFH-capable occupations. As such, improved access to WFH arrangements during the pandemic appears to have been more of a novelty for people *without* disability than for the disability population in Australia, at least compared to the US experience. In addition, although low, Australian disability employment rates have still been historically higher (at about 50%) than in the US (at about 35-40%; Bloom et al., 2026), suggesting the US had more opportunities to improve access to employment for people with disability.²⁵

Overall, the paper’s findings suggest that, although flexible work is an important mechanism supporting workforce engagement for many people with disability, increased WFH access was

²⁵ Some of this difference may also be attributable to different measures and definitions of disability.

not the main driver of improved disability employment after 2020. Instead, the available evidence suggests that tighter labour markets, employer demand, and broader willingness to hire are more important for driving greater disability employment at the margin. For public policy, this reinforces the importance of full employment as a mechanism to support labour market engagement for disadvantaged cohorts, while policy settings should still ensure that people with disability can access flexible working arrangements when needed. Future work on this topic could expand on whether there are remaining barriers to WFH uptake or downsides from its use (such as social isolation, stigma or career and pay implications) that mean people with disability and their employers remain reluctant to adopt remote working arrangements. This would include complementing the quantitative analysis above with greater reliance on qualitative sources from those with lived experience to better understand employment drivers and WFH impacts for people with disability.

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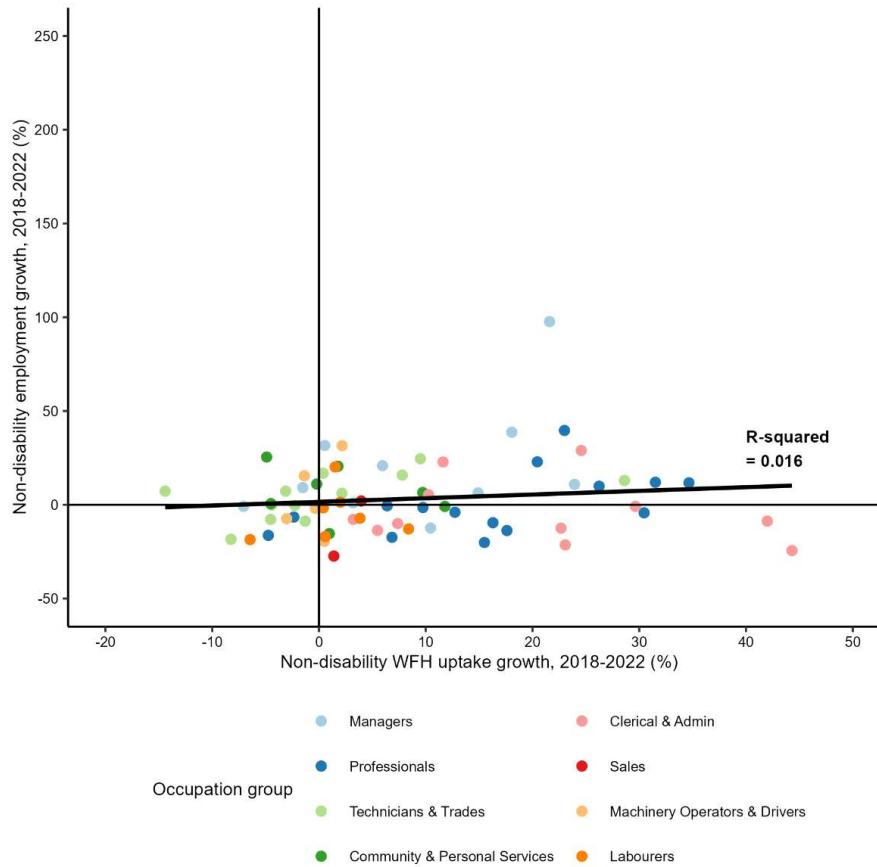
Appendix A: Supplementary materials for SDAC analysis

Table A.1: SDAC population composition changes, 2018 to 2022

Variable	Category level	Population share, 2018 (%)	Population share, 2022 (%)	Change 2018-22 (ppts)
Age category	15-24	15.61	15.47	-0.14
	25-34	24.75	24.44	-0.30
	35-44	22.67	23.87	1.19
	45-54	21.40	21.03	-0.37
	55-64	15.57	15.19	-0.38
Education category	No post-secondary	33.63	31.01	-2.62
	Vocational education	31.50	30.19	-1.31
	University degree	34.87	38.81	3.94
Gender	Male	52.29	52.11	-0.18
	Female	47.71	47.89	0.18

Note: Shares weighted by ABS population weights. Data sourced from the 2018 and 2022 waves of SDAC.

Figure A.1: Non-disability employment growth v WFH growth



Notes: Chart depicts the relationship between non-disability employment growth in each occupation between the 2018 and 2022 waves of SDAC, and the change in the proportion of the non-disability population undertaking any WFH in those occupations between 2018 and 2022. Only occupations with 10 or more disability observations are included, for data confidentiality reasons.

Table A.2: IV results – full-time and part-time disability employment

Panel A: Full-time employment

Dependent variable: Change in full-time disability employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in WFH	1.730*	1.480*	1.529*	1.542*	0.707	0.176	0.083	0.146
	(0.714)	(0.712)	(0.696)	(0.686)	(1.452)	(1.488)	(1.497)	(1.459)
First-stage instrument					22.430***	22.272***	22.074***	22.064***
					(3.076)	(3.294)	(3.050)	(3.105)
Occupation cells	89	89	89	89	89	89	89	89
First-stage F-statistic					57.21	52.93	56.05	53.35

Panel B: Part-time employment

Dependent variable: Change in part-time disability employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in WFH	4.925	4.946	4.944	4.959	8.996	8.944	9.244	9.417
	(4.532)	(4.621)	(4.482)	(4.510)	(6.436)	(7.142)	(6.328)	(6.969)
First-stage instrument					22.350***	22.451***	22.007***	21.750***
					(3.092)	(3.274)	(3.066)	(3.164)
Occupation cells	88	88	88	88	88	88	88	88
First-stage F-statistic					55.59	54.30	54.51	51.55
Labour market controls		X		X		X		X
Compositional controls			X	X			X	X
2SLS approach					X	X	X	X

Note: The dependent variables are the change in the count of people with a disability employed full-time (panel A) or part-time (panel B) in an occupation between the 2018 and 2022 SDAC waves, using ABS-provided survey weights. All other variables are the same as described in Table 1. Heteroskedasticity-robust standard errors are in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.3: IV sensitivity analysis – non-psychosocial disability only

Dependent variable: Change in disability employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in WFH	1.546* (0.619)	1.086+ (0.623)	1.440* (0.596)	1.368* (0.601)	0.956 (1.067)	0.067 (1.062)	0.654 (1.051)	0.532 (1.047)
First-stage instrument					22.250*** (3.114)	21.440*** (3.452)	21.933*** (3.087)	21.598*** (3.220)
Labour market controls		X		X		X		X
Compositional controls			X	X			X	X
2SLS approach					X	X	X	X
Occupation cells	83	83	83	83	83	83	83	83
Outcome regression R^2	0.057	0.148	0.051	0.094	0.009	0.122	0.004	0.051
First-stage F-statistic					52.09	44.68	51.27	47.35

Note: Sensitivity analysis using only the SDAC disability sub-sample who do not report having a psychosocial disability in each of the 2018 and 2022 waves. All other variables are the same as described in Table 1. Heteroskedasticity-robust standard errors are in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.4: IV sensitivity analysis – majority WFH arrangements

Dependent variable: Change in disability employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change in majority WFH	0.998*	0.472	0.880+	0.668	0.637	0.110	0.518	0.464
	(0.492)	(0.481)	(0.477)	(0.475)	(0.755)	(0.789)	(0.753)	(0.746)
First-stage instrument					28.761***	26.653***	28.465***	27.688***
					(4.098)	(4.091)	(4.052)	(3.904)
Labour market controls		X		X		X		X
Compositional controls			X	X			X	X
IV approach					X	X	X	X
Occupation cells	89	89	89	89	89	89	89	89
Outcome regression R^2	0.034	0.114	0.026	0.073	0.007	0.108	0.005	0.062
First-stage F-statistic					87.35	81.71	87.86	90.98

Note: Sensitivity analysis using a main independent variable that measures the change in the share of people without a disability in an occupation who reported that they ‘usually work most hours at home’ in 2022 versus 2018 within the SDAC. All other variables are the same as described in Table 1. Heteroskedasticity-robust standard errors are in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

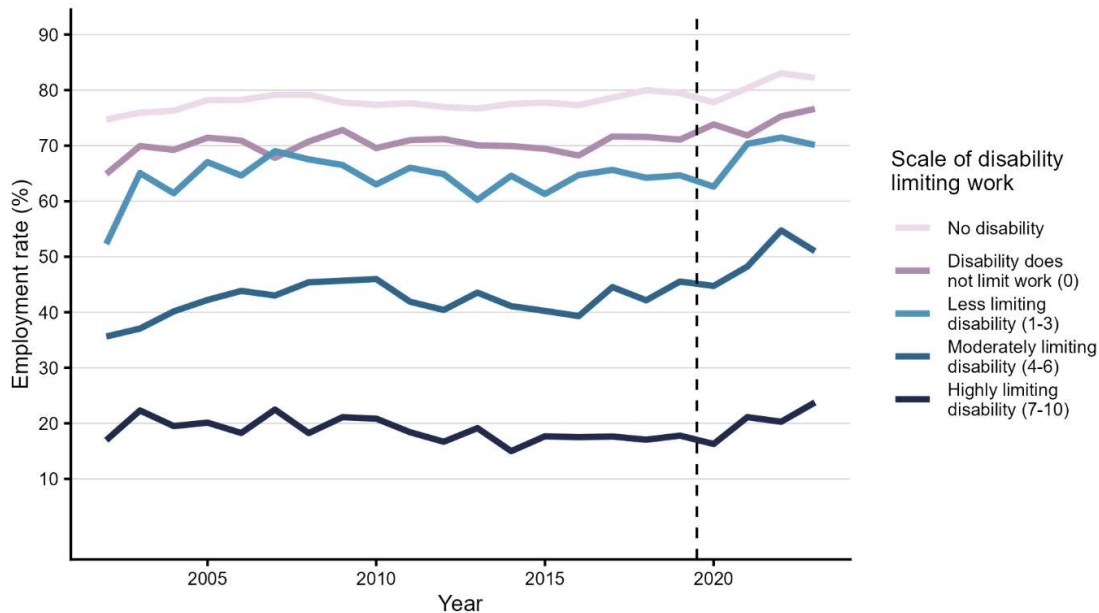
Table A.5: IV sensitivity analysis – compositional controls without NDIS

Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Change in total disability employment ($\% \Delta \text{employ}_j^d$)		Change in full-time disability employment ($\% \Delta \text{FTEmploy}_j^d$)		Change in part-time disability employment ($\% \Delta \text{PTemploy}_j^d$)	
Change in WFH (ΔWFH_j^n)	1.252*	0.303	1.534*	-0.001	4.694	8.424
	(0.508)	(0.979)	(0.707)	(1.505)	(4.470)	(6.339)
IV approach		X		X		X
Occupation cells	89	89	89	89	88	88

Note: Sensitivity analysis using compositional controls that do not include NDIS effects – that is, the inverse propensity score weight is based on fully-interacted regression models for age (5 categories), gender (2 categories) and education (3 categories) only. All other variables are the same as described in Table 1. Heteroskedasticity-robust standard errors are in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

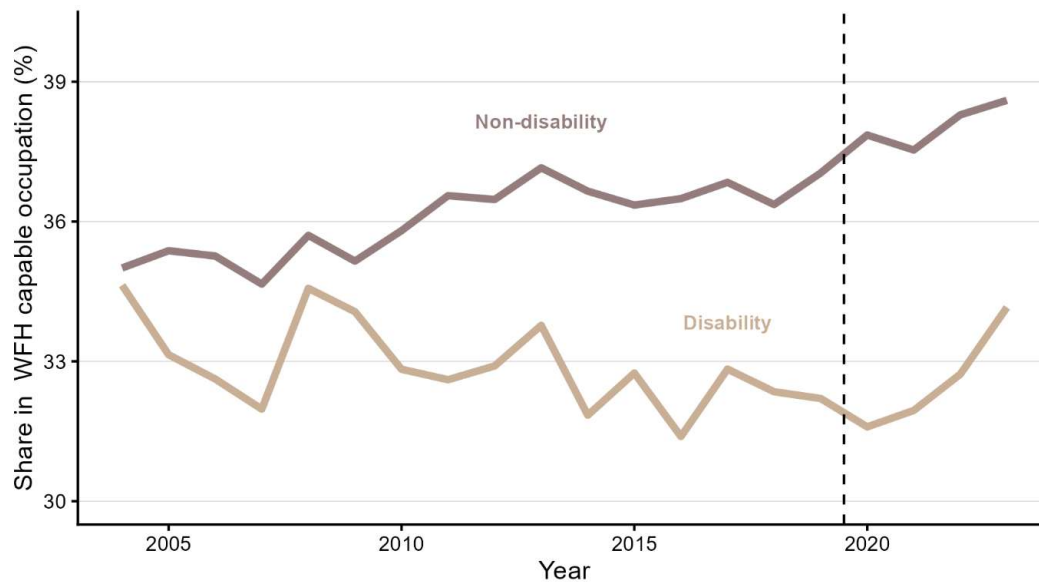
Appendix B: Supplementary materials for HILDA analysis

Figure B.1: Employment rates, by work-limiting disability and severity



Notes: Chart depicts the sample employment rate ($\frac{\text{working-age employed}}{\text{working-age population}}$), split between the sub-samples with: no disability; a disability that is not work-limiting; a disability that is work-limiting, which is subsequently divided between low, moderate and high degrees of work limitation, based on a self-assessed 1-10 scale. Dotted line denotes the start of the COVID-19 pandemic in 2020. Source: HILDA survey, waves 4 to 23.

Figure B.2: Share of employed in WFH-capable occupations, by disability status



Note: Chart depicts the share of employed individuals in a WFH-capable occupation (a Dingel-Neiman score greater than or equal to 0.5), split between those with and without a functional disability each year. Dotted line denotes the start of the COVID-19 pandemic in 2020. Source: Dingel & Neiman (2020) and HILDA survey, waves 4 to 23.

Table B.1: Summary statistics for HILDA sample, by disability criteria

Disability criteria:	$Disability_i = 1$	$Disability_i = 0$	$DN_i^{pre} = 0$	$DN_i^{pre} = 0.25$	$DN_i^{pre} = 0.5$	$DN_i^{pre} = 0.75$	$DN_i^{pre} = 1$
Employment status:							
Total employment rate	40.7%	83.0%	76.9%	82.5%	77.7%	80.8%	83.8%
Full-time employment rate	22.5%	58.4%	49.7%	58.7%	50.2%	60.2%	63.8%
Part-time employment rate	18.2%	24.6%	27.2%	23.7%	27.5%	20.7%	20.0%
Unemployment rate	4.8%	2.9%	4.0%	1.4%	2.5%	1.8%	1.9%
Not in labour force (NILF)	54.5%	14.2%	19.1%	16.1%	19.8%	17.4%	14.3%
Usual weekly hours (main job)	13.0	30.2	26.9	31.4	26.0	30.0	31.7
- conditional on employment	31.9	36.4	35.0	38.1	33.4	37.1	37.8
Mean wage (main job, if employed)	\$35.5	\$41.3	\$34.8	\$40.7	\$36.7	\$49.1	\$49.3
WFH status							
Share in WFH-capable occup. pre-pandemic	26.5%	37.9%	0.00	0.25	0.50	0.75	1.00
Share in WFH-capable occup. post-pandemic	26.7%	40.6%	0.09	0.33	0.49	0.70	0.88
Share with any WFH uptake pre-pandemic	11.2%	20.8%	10.6%	28.2%	16.7%	33.2%	37.8%
Share with any WFH uptake post-pandemic	14.7%	32.4%	14.3%	38.0%	35.6%	52.2%	54.9%
Mean proportion of WFH hours (if employed)	16.6%	15.2%	6.1%	20.1%	18.9%	27.4%	27.8%
Disability status							
Share with functional disability	92.6%	4.5%	26.2%	23.6%	26.1%	19.2%	18.6%
Share with work-limiting disability	74.3%	2.1%	17.4%	15.1%	17.3%	11.5%	10.2%
Mean scale of work-limiting disability (-1 to 10)	4.52	-0.85	0.25	-0.04	0.18	-0.20	-0.33
Share receiving NDIS support	5.8%	0.1%	0.9%	0.5%	1.4%	0.5%	0.6%
Other demographics							
Mean age (years)	49.9	40.6	40.9	45.7	44.5	46.4	45.0
Female share	57.2%	51.8%	45.8%	54.2%	75.0%	61.3%	54.4%
Share with university degree	18.6%	36.2%	17.2%	38.0%	40.4%	46.7%	61.9%
Observations	12,272	54,234	44,413	5,744	4,550	5,394	20,025
Individuals	1,958	8,417	7,300	933	725	880	3,162

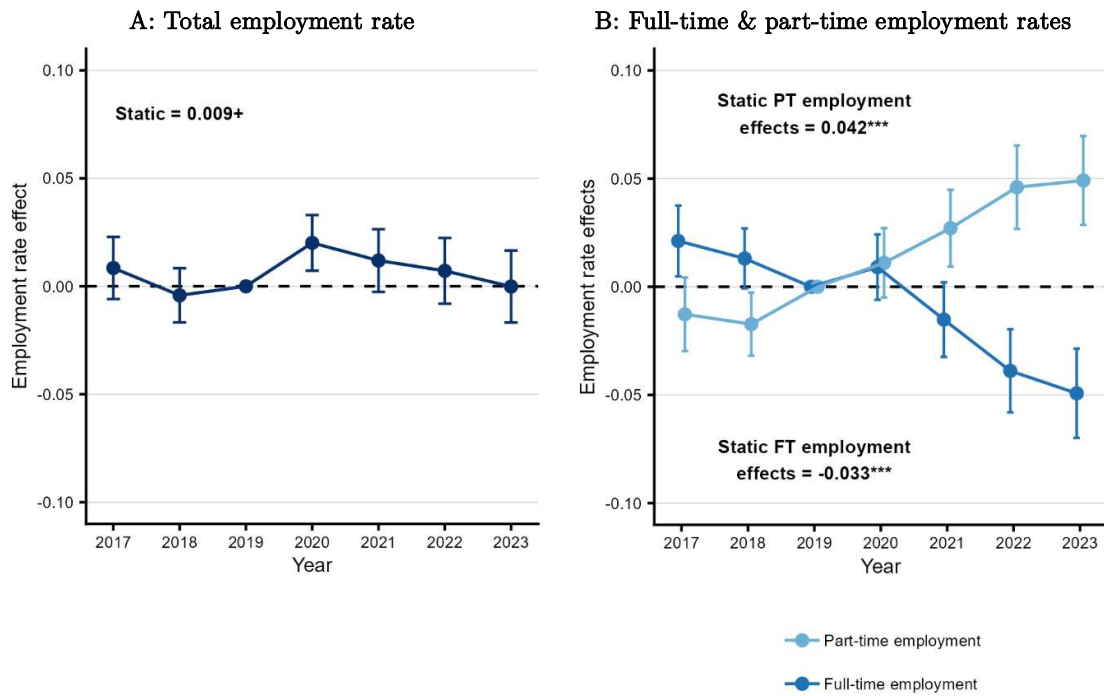
Note: Data sourced from HILDA, based on a balanced sample from waves 17–23. Disability severity scale includes score of -1 if no disability, 0 if non-work-limiting disability, and 1 to 10 for work-limiting disability.

Table B.2: WFH-capability DiD regression results

Dependent variable:	(1) Employment rate	(2) Full-time employment rate	(3) Part-time employment rate
Teleworkability score			
t = -3 (2017)	0.008 (0.007)	0.021* (0.008)	-0.013 (0.009)
t = -2 (2018)	-0.004 (0.006)	0.013+ (0.007)	-0.017* (0.007)
t = 0 (2020)	0.020** (0.007)	0.009 (0.008)	0.011 (0.008)
t = 1 (2021)	0.012 (0.007)	-0.015+ (0.009)	0.027** (0.009)
t = 2 (2022)	0.007 (0.008)	-0.039*** (0.010)	0.046*** (0.010)
t = 3 (2023)	-0.000 (0.009)	-0.049*** (0.011)	0.049*** (0.010)
<i>Static treatment effect</i>	<i>0.009+</i> <i>(0.005)</i>	<i>-0.033***</i> <i>(0.007)</i>	<i>0.042***</i> <i>(0.007)</i>
Age-squared	-0.001*** (0.000)	-0.001*** (0.000)	0.000*** (0.000)
Observations	80,126	80,126	80,126
R^2	0.668	0.694	0.557

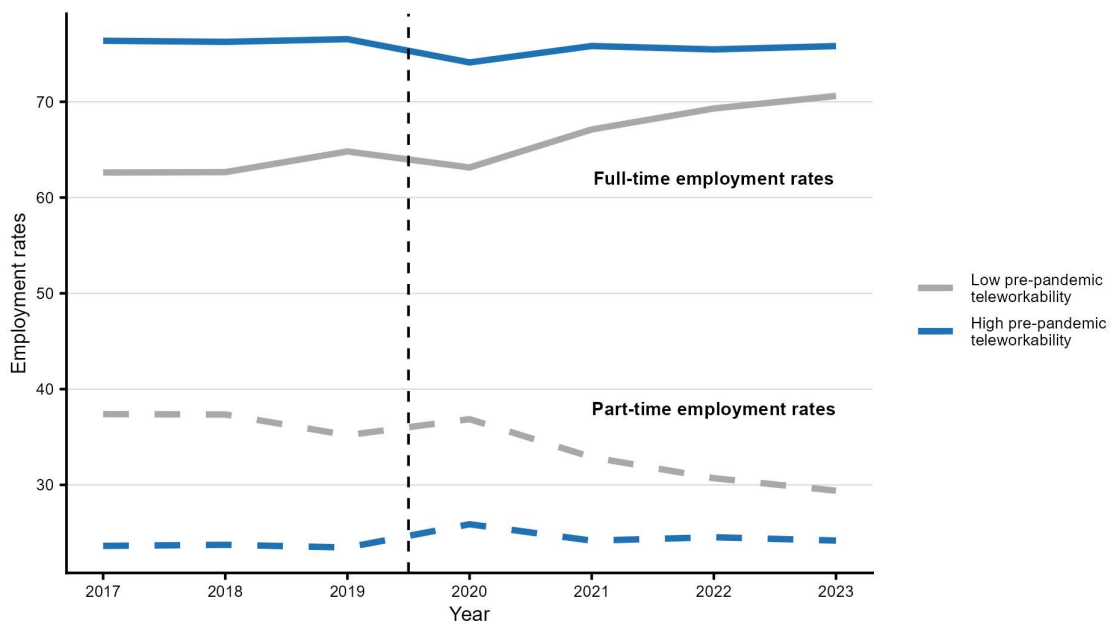
Note: Regression results for a DiD specification on the pre-pandemic WFH-capability estimator (DN_i^{pre}). Static (italicised) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include fixed effects at the individual and year level. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Figure B.3: WFH-capability DiD event study plots



Note: Event study plots for pre-pandemic WFH-capability (DN_i^{pre}) in a DiD specification, split by dependent variables. Effects measured against 2019 pre-treatment baseline, error bars represent 95% confidence intervals, standard errors clustered at individual level. Data sourced from HILDA, waves 17–23.

Figure B.4: Parallel trends by pre-pandemic WFH-capability status



Note: Chart depicts full-time and part-time employment rates, split by pre-pandemic teleworkability scores (above or below 0.5, exclusive). Source: Dingel & Neiman (2020) and HILDA survey, waves 17 to 23.

Table B.3: DDD heterogeneity analysis – gender and age groups

Sub-sample: Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Employ. rate	Male FT employ. rate	PT employ. rate	Employ. rate	Female FT employ. rate	PT employ. rate	Employ. rate	45 and under FT employ. rate	PT employ. rate	Employ. rate	Over 45 FT employ. rate	PT employ. rate
Disability x pre-pandemic teleworkability score	-0.051+ (0.028)	-0.001 (0.029)	-0.050+ (0.028)	-0.029 (0.027)	0.025 (0.028)	-0.054+ (0.032)	-0.018 (0.035)	0.031 (0.039)	-0.049 (0.042)	-0.025 (0.026)	-0.008 (0.025)	-0.017 (0.028)
Disability	0.034* (0.015)	0.036* (0.015)	-0.002 (0.015)	0.027+ (0.016)	0.004 (0.015)	0.023 (0.018)	0.044* (0.018)	-0.006 (0.018)	0.050* (0.020)	0.027+ (0.015)	0.040** (0.014)	-0.013 (0.016)
Pre-pandemic teleworkability score	0.008 (0.008)	-0.026* (0.011)	0.034*** (0.009)	0.021* (0.010)	-0.039** (0.013)	0.060*** (0.014)	0.004 (0.008)	-0.040*** (0.012)	0.044*** (0.011)	0.009 (0.011)	-0.007 (0.014)	0.016 (0.013)
Observations	28,948			30,809			34,122			25,297		
R^2	0.677	0.693	0.502	0.671	0.649	0.540	0.540	0.645	0.522	0.769	0.761	0.623

Note: Static DDD regression results by heterogeneity sub-sample, split by gender (male or female) or by age (45 and under or over 45). Effects measured against 2019 pre-treatment baseline. All regressions include controls for age-squared, NDIS support and individual and year fixed effects. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.4: DDD heterogeneity analysis – DSP recipient status

Disability definition: Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Disability Support Pension (DSP) recipient Employment rate	Full-time employment rate	Part-time employment rate	Non-DSP recipient with disability Employment rate	Full-time employment rate	Part-time employment rate
Disability x pre-pandemic teleworkability score						
t = -3 (2017)	0.012 (0.066)	-0.003 (0.046)	0.015 (0.052)	0.004 (0.029)	-0.018 (0.029)	0.022 (0.033)
t = -2 (2018)	-0.096+ (0.050)	-0.021+ (0.011)	-0.075 (0.051)	-0.008 (0.025)	-0.052* (0.024)	0.044 (0.028)
t = 0 (2020)	-0.041 (0.066)	0.018 (0.023)	-0.059 (0.066)	-0.003 (0.025)	0.003 (0.025)	-0.006 (0.031)
t = 1 (2021)	-0.096+ (0.050)	0.024 (0.027)	-0.120** (0.046)	-0.026 (0.030)	0.018 (0.031)	-0.045 (0.035)
t = 2 (2022)	-0.132* (0.060)	0.042 (0.033)	-0.175** (0.057)	-0.047 (0.031)	-0.013 (0.034)	-0.034 (0.036)
t = 3 (2023)	-0.087 (0.085)	0.092 (0.062)	-0.179** (0.065)	-0.060+ (0.036)	-0.053 (0.038)	-0.007 (0.042)
<i>Static treatment effect</i>	<i>-0.060 (0.040)</i>	<i>0.050* (0.024)</i>	<i>-0.110** (0.039)</i>	<i>-0.030 (0.022)</i>	<i>0.016 (0.023)</i>	<i>-0.046+ (0.025)</i>
<i>Disability (static)</i>	<i>0.100*** (0.020)</i>	<i>0.059*** (0.013)</i>	<i>0.041* (0.020)</i>	<i>0.018 (0.012)</i>	<i>0.012 (0.013)</i>	<i>0.007 (0.014)</i>
<i>Pre-pandemic teleworkability score (static)</i>	<i>0.014* (0.006)</i>	<i>-0.030*** (0.009)</i>	<i>0.044*** (0.008)</i>	<i>0.015* (0.006)</i>	<i>-0.031*** (0.009)</i>	<i>0.046*** (0.008)</i>
Observations	51,582	51,582	51,582	57,804	57,804	57,804
R ²	0.632	0.678	0.556	0.650	0.684	0.553

Note: DDD regression results by dependent variable, where the treated groups are identified as people with consistent pre-pandemic disability who were also receiving DSP in all pre-pandemic years (columns 1–3) or those who were not receiving the DSP in any pre-pandemic year (columns 4–6). Static (*italicised*) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include controls for age-squared, NDIS support and individual and year fixed effects. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table B.5: DDD sensitivity analysis – alternate work-limiting disability definition

Disability definition: Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Employ. rate	FT employ. rate	PT employ. rate	Employ. rate	FT employ. rate	PT employ. rate	Employ. rate	FT employ. rate	PT employ. rate
Disability x pre-pandemic telework. score									
t = -3 (2017)	0.025 (0.036)	0.014 (0.031)	0.010 (0.038)	0.009 (0.049)	0.008 (0.040)	0.001 (0.052)	0.048 (0.105)	-0.116 (0.097)	0.164 (0.117)
t = -2 (2018)	0.009 (0.029)	-0.031 (0.025)	0.040 (0.031)	-0.043 (0.043)	-0.042 (0.029)	-0.002 (0.046)	0.065 (0.091)	-0.048 (0.094)	0.114 (0.107)
t = 0 (2020)	-0.001 (0.030)	0.018 (0.028)	-0.019 (0.038)	-0.025 (0.040)	0.021 (0.038)	-0.046 (0.047)	0.125+ (0.073)	0.103 (0.088)	0.022 (0.111)
t = 1 (2021)	-0.033 (0.036)	0.007 (0.033)	-0.040 (0.041)	-0.028 (0.049)	0.024 (0.047)	-0.051 (0.048)	-0.023 (0.097)	-0.043 (0.117)	0.021 (0.135)
t = 2 (2022)	-0.072* (0.036)	-0.009 (0.036)	-0.063 (0.041)	-0.094* (0.045)	0.035 (0.033)	-0.129** (0.047)	0.007 (0.089)	-0.092 (0.133)	0.099 (0.108)
t = 3 (2023)	-0.103* (0.044)	-0.041 (0.039)	-0.062 (0.046)	-0.075 (0.061)	0.049 (0.041)	-0.124* (0.059)	0.135 (0.110)	-0.116 (0.128)	0.251* (0.116)
<i>Static treatment effect</i>	<i>-0.059*</i> <i>(0.026)</i>	<i>0.002</i> <i>(0.025)</i>	<i>-0.061*</i> <i>(0.029)</i>	<i>-0.041</i> <i>(0.034)</i>	<i>0.042</i> <i>(0.031)</i>	<i>-0.083*</i> <i>(0.037)</i>	<i>0.023</i> <i>(0.056)</i>	<i>0.021</i> <i>(0.077)</i>	<i>0.002</i> <i>(0.071)</i>
<i>Disability (static)</i>	<i>0.054***</i> <i>(0.014)</i>	<i>0.048***</i> <i>(0.012)</i>	<i>0.006</i> <i>(0.014)</i>	<i>0.071***</i> <i>(0.018)</i>	<i>0.066***</i> <i>(0.013)</i>	<i>0.005</i> <i>(0.017)</i>	<i>-0.029</i> <i>(0.036)</i>	<i>-0.021</i> <i>(0.047)</i>	<i>-0.008</i> <i>(0.046)</i>
<i>Pre-pandemic telework. score (static)</i>	<i>0.014*</i> <i>(0.006)</i>	<i>-0.031***</i> <i>(0.009)</i>	<i>0.045***</i> <i>(0.008)</i>	<i>0.014*</i> <i>(0.006)</i>	<i>-0.031***</i> <i>(0.009)</i>	<i>0.045***</i> <i>(0.008)</i>	<i>0.014*</i> <i>(0.006)</i>	<i>-0.030***</i> <i>(0.009)</i>	<i>0.044***</i> <i>(0.008)</i>
Observations	56,022	56,022	56,022	53,276	53,276	53,276	50,990	50,990	50,990
R ²	0.673	0.693	0.556	0.658	0.687	0.557	0.602	0.669	0.555

Note: DDD regression results by dependent variable, split between alternate *Disability_i* definitions based on work-limiting disability. ‘Severe’ work-limiting disability defined as score of 5 or greater on self-identified 0–10 scale, ‘moderate’ work-limiting disability defined as score of less than 5. Static (*italicised*) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include controls for age-squared, NDIS support and individual and year fixed effects. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table B.6: DDD sensitivity analysis – alternate disability persistence definitions

Disability definition: Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
	Employment rate	Full-time employment rate	Part-time employment rate	Employment rate	Full-time employment rate	Part-time employment rate
Disability x pre-pandemic teleworkability score						
t = -3 (2017)	-0.002 (0.017)	0.011 (0.018)	-0.012 (0.019)	0.023 (0.035)	0.009 (0.029)	0.013 (0.035)
t = -2 (2018)	-0.010 (0.014)	-0.004 (0.015)	-0.006 (0.016)	0.006 (0.028)	-0.029 (0.022)	0.035 (0.029)
t = 0 (2020)	-0.025+ (0.015)	-0.001 (0.016)	-0.024 (0.018)	0.008 (0.030)	0.035 (0.026)	-0.028 (0.035)
t = 1 (2021)	-0.019 (0.017)	0.015 (0.019)	-0.034+ (0.020)	0.012 (0.034)	0.058+ (0.032)	-0.046 (0.039)
t = 2 (2022)	-0.023 (0.018)	0.008 (0.021)	-0.031 (0.021)	-0.002 (0.035)	0.067+ (0.035)	-0.069+ (0.041)
t = 3 (2023)	-0.040* (0.020)	-0.001 (0.023)	-0.039+ (0.023)	-0.032 (0.043)	0.037 (0.040)	-0.069 (0.047)
<i>Static treatment effect</i>	<i>-0.022+ (0.012)</i>	<i>0.003 (0.015)</i>	<i>-0.025+ (0.014)</i>	<i>-0.011 (0.025)</i>	<i>0.056* (0.024)</i>	<i>-0.067* (0.028)</i>
<i>Disability (static)</i>	<i>0.014+ (0.007)</i>	<i>0.006 (0.008)</i>	<i>0.007 (0.008)</i>	<i>0.017 (0.013)</i>	<i>0.001 (0.012)</i>	<i>0.016 (0.014)</i>
<i>Pre-pandemic teleworkability score (static)</i>	<i>0.015* (0.006)</i>	<i>-0.032*** (0.009)</i>	<i>0.047*** (0.008)</i>	<i>0.015* (0.006)</i>	<i>-0.040*** (0.009)</i>	<i>0.055*** (0.009)</i>
Observations	77,121	77,121	77,121	49,666	49,666	49,666
R ²	0.670	0.694	0.555	0.685	0.700	0.565

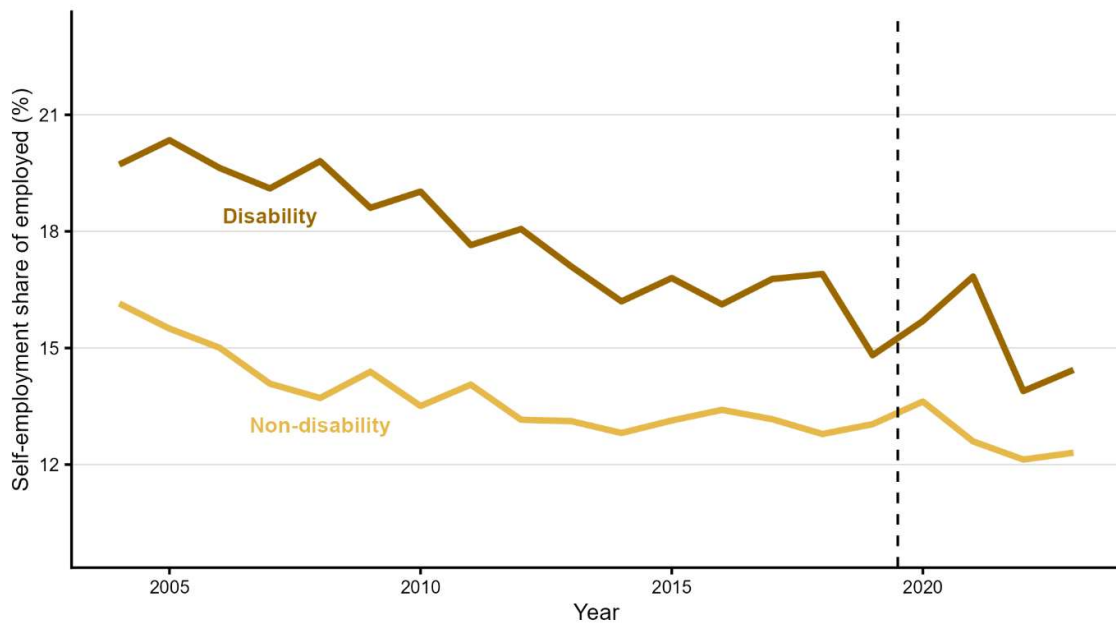
Note: DDD regression results by dependent variable, split between alternate definitions of disability persistence for $Disability_{it}$. Static (*italicised*) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include controls for age-squared, NDIS support and individual and year fixed effects. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Table B.7: DDD sensitivity analysis – disability types

Disability treatment group: Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Non-psychosocial disability			Non-sensory disability			Non-physical disability		
	Employ. rate	FT employ. rate	PT employ. rate	Employ. rate	FT employ. rate	PT employ. rate	Employ. rate	FT employ. rate	PT employ. rate
Disability x pre-pandemic teleworkability score	-0.038+ (0.022)	0.014 (0.023)	-0.052* (0.025)	-0.032 (0.021)	0.019 (0.022)	-0.050* (0.024)	-0.054* (0.025)	0.017 (0.028)	-0.071* (0.029)
Disability	0.018 (0.012)	0.020 (0.012)	-0.002 (0.013)	0.030* (0.012)	0.023+ (0.012)	0.007 (0.013)	0.034* (0.015)	0.008 (0.015)	0.026 (0.017)
Pre-pandemic teleworkability score	0.013* (0.006)	-0.032*** (0.009)	0.045*** (0.008)	0.014* (0.006)	-0.032*** (0.009)	0.046*** (0.008)	0.011+ (0.006)	-0.034*** (0.009)	0.045*** (0.008)
Observations	56,944	56,944	56,944	57,791	57,791	57,791	53,685	53,685	53,685
R^2	0.664	0.690	0.560	0.664	0.690	0.555	0.638	0.682	0.563

Note: Static DDD regression results by dependent variable, using a disability treatment group that excludes any respondents with a condition that is psychosocial (a mental illness and/or a nervous or emotional disorder), sensory (speech, sight or hearing conditions), or physical (blackouts, limitations of the arm, leg or grip, disfigurements, chronic pain, and/or shortness of breath). Effects measured against 2019 pre-treatment baseline. All regressions include controls for age-squared, NDIS support and individual and year fixed effects. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure B.5: Self-employment shares, by disability status



Notes: Chart depicts the share of employed working-age individuals who were self-employed, split between those with and without a functional disability each year. Dotted line denotes the start of the COVID-19 pandemic in 2020. Source: HILDA survey, waves 4 to 23.

Table B.8: DDD sensitivity analysis – self-employment

Dependent variable:	(1) Self-employment	(2) Non-self-employment
Disability x pre-pandemic teleworkability score		
t = -3 (2017)	0.018 (0.016)	-0.011 (0.027)
t = -2 (2018)	0.002 (0.014)	-0.011 (0.023)
t = 0 (2020)	0.017 (0.014)	-0.021 (0.023)
t = 1 (2021)	0.028 (0.017)	-0.059* (0.028)
t = 2 (2022)	0.017 (0.020)	-0.069* (0.031)
t = 3 (2023)	0.005 (0.021)	-0.074* (0.033)
<i>Static treatment effect</i>	<i>0.011</i> <i>(0.013)</i>	<i>-0.046*</i> <i>(0.021)</i>
<i>Disability (static)</i>	<i>-0.004</i> <i>(0.007)</i>	<i>0.034**</i> <i>(0.011)</i>
<i>Pre-pandemic teleworkability score (static)</i>	<i>-0.004</i> <i>(0.005)</i>	<i>0.019**</i> <i>(0.007)</i>
Observations	59,757	59,757
R^2	0.746	0.703

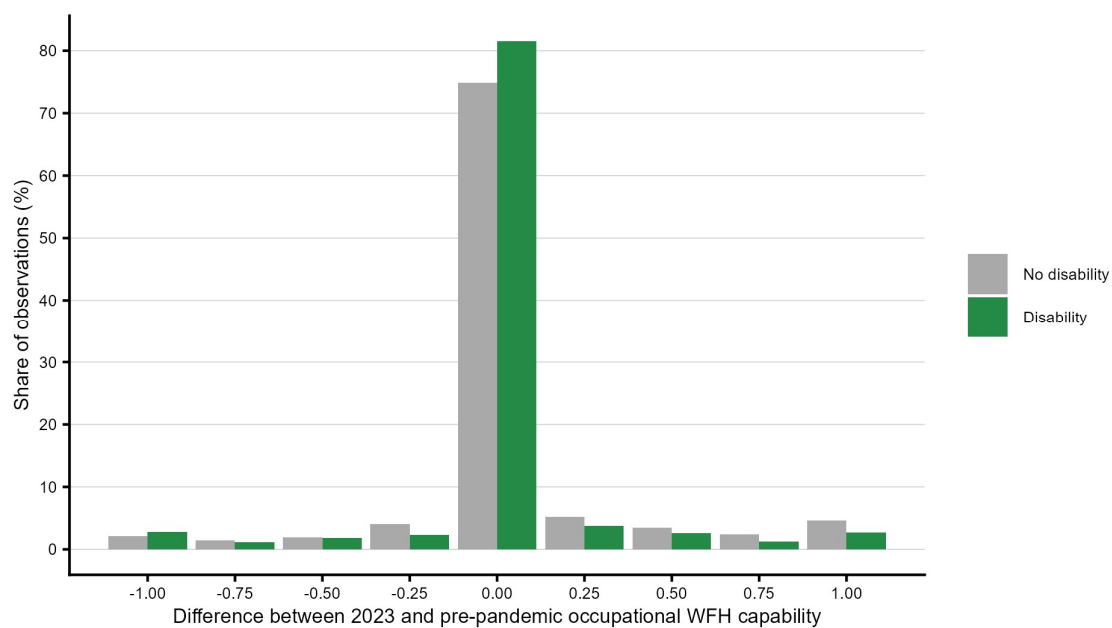
Note: DDD regression results by self-employment outcome or non-self-employment (i.e. employee) outcome. Static (*italicised*) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include fixed effects at the individual and year level. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B.9: DDD sensitivity analysis – stable WFH capability over time

Dependent variable:	(1) Employment rate	(2) Full-time employment rate	(3) Part-time employment rate
Disability x stable teleworkability score			
t = -3 (2017)	0.030 (0.032)	-0.014 (0.028)	0.043 (0.032)
t = -2 (2018)	0.002 (0.026)	-0.014 (0.021)	0.016 (0.026)
t = 0 (2020)	-0.015 (0.027)	0.009 (0.024)	-0.024 (0.032)
t = 1 (2021)	-0.020 (0.028)	0.051+ (0.027)	-0.071* (0.031)
t = 2 (2022)	-0.069* (0.031)	-0.018 (0.033)	-0.051 (0.034)
t = 3 (2023)	-0.070+ (0.037)	-0.004 (0.039)	-0.066 (0.040)
<i>Static treatment effect</i>	<i>-0.050*</i> <i>(0.023)</i>	<i>0.022</i> <i>(0.024)</i>	<i>-0.072**</i> <i>(0.025)</i>
<i>Disability (static)</i>	<i>0.042***</i> <i>(0.012)</i>	<i>0.032**</i> <i>(0.011)</i>	<i>0.010</i> <i>(0.012)</i>
<i>Stable teleworkability score (static)</i>	<i>0.008</i> <i>(0.008)</i>	<i>-0.018+</i> <i>(0.011)</i>	<i>0.026**</i> <i>(0.010)</i>
Observations	38,941	38,941	38,941
R ²	0.725	0.736	0.575

Note: DDD regression results by dependent variable, using only the sub-sample of individuals with an identical WFH-capability score across all observations. Static (*italicised*) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include fixed effects at the individual and year level. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.

Figure B.6: Occupational WFH-capability changes over time



Note: Share of observations by change in occupational WFH capability, calculated as an individual's 2023 WFH capability values less their modal pre-pandemic status (DN_i^{pre}), split by disability status. Data sourced from HILDA, waves 17–23.

Table B.10: DDD sensitivity analysis – balanced panel

Dependent variable:	(1) Employment rate	(2) Full-time employment rate	(3) Part-time employment rate
Disability x pre-pandemic teleworkability score			
t = -3 (2017)	0.022 (0.031)	0.001 (0.030)	0.021 (0.036)
t = -2 (2018)	0.015 (0.025)	-0.030 (0.024)	0.045 (0.029)
t = 0 (2020)	0.032 (0.027)	0.015 (0.025)	0.016 (0.032)
t = 1 (2021)	-0.026 (0.030)	0.008 (0.030)	-0.033 (0.035)
t = 2 (2022)	-0.035 (0.030)	0.005 (0.032)	-0.040 (0.034)
t = 3 (2023)	-0.048 (0.034)	-0.026 (0.035)	-0.022 (0.038)
<i>Static treatment effect</i>	<i>-0.035</i> <i>(0.022)</i>	<i>0.011</i> <i>(0.023)</i>	<i>-0.046+</i> <i>(0.025)</i>
<i>Disability (static)</i>	<i>0.032**</i> <i>(0.012)</i>	<i>0.019</i> <i>(0.012)</i>	<i>0.014</i> <i>(0.013)</i>
<i>Pre-pandemic teleworkability score (static)</i>	<i>0.011+</i> <i>(0.007)</i>	<i>-0.037***</i> <i>(0.009)</i>	<i>0.048***</i> <i>(0.009)</i>
Observations	55,356	55,356	55,356
R ²	0.647	0.682	0.547

Note: DDD regression results by dependent variable, using a balanced panel of individuals observed across all periods. Static (*italicised*) and dynamic effects measured against 2019 pre-treatment baseline. All regressions include fixed effects at the individual and year level. Standard errors (in parentheses) are clustered at the individual level. Data sourced from HILDA, waves 17–23. + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001.