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Beyond lockdowns: work-from-home, mental health, and the moderating roles of intensity, job control and social support

Anam Bilgrami[1,2,3]

Abstract:

During and shortly after the height of the COVID-19 pandemic, concerns were expressed that working from home (WFH) was creating a 'mental health crisis'. Australia experienced a three-phase 'WFH experiment', with widespread high-intensity WFH imposed by lockdowns in 2020, deepened restrictions in 2021, and a transition to flexible work arrangements and more autonomy in 2022 as vaccination rates increased. Using data from the Household, Income and Labour Dynamics in Australia survey, this study estimates the impact of WFH on worker mental health across these phases. Findings show that WFH led to a modest, statistically significant deterioration in average worker mental health outcomes during the lockdown years (2020–2021), particularly among women. Negative effects were present in workers across the social support and job control spectrum, suggesting limited buffering capacity to counter the stress of lockdown restrictions. However, by 2022, the negative effects of WFH dissipated with positive effects for those WFH 25-50% of time, indicating that pandemic-related lockdowns, rather than WFH itself, were primarily responsible for

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[2] **Data:** This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either DSS or the Melbourne Institute.

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mental health declines. The exception was workers with low job control, and females with dependents, who continued to experience negative effects, highlighting that job autonomy and unequal caregiving responsibilities may shape longer-term wellbeing outcomes.

JEL: D02, I12, L23

Introduction

During and shortly after the height of the COVID-19 pandemic, concerns were expressed that the advent of frequent working from home (WFH) was creating a 'rapidly growing mental health crisis'[1]. Indeed, the pandemic was the catalyst for the rapid adoption of high-intensity WFH across many countries. This was driven largely by public health mandates and lockdowns aimed at limiting movement and curbing infection spread over 2020 and 2021. This shift to WFH was particularly pronounced in Australia, where strict lockdowns led to a sharp increase in WFH adoption among workers and a corresponding rise in employers offering remote work arrangements. Notably, the city of Melbourne in Victoria earned the distinction of being the 'world's most locked-down city' (Macreadie, 2022), highlighting the extent of the restrictions on public mobility in Australia.

Nonetheless, this large-scale 'mandated' take-up indirectly revealed the potential benefits and feasibility of remote work to both employers and workers, encouraging some employers to adopt new technologies and offer formal remote work arrangements, enabling WFH beyond the initial period of lockdowns over 2020-21 (Productivity Commission, 2021).

With these recent dramatic changes in the world of work, a growing empirical literature is investigating the impacts of WFH on workers and firms, including on worker health and wellbeing (Lunde et al., 2022; Oakman et al., 2020). This includes recent studies with robust causal identification techniques that have identified negative mental health effects from WFH during lockdowns, including amongst older populations and women (Bertoni et al., 2025; Gueguen & Senik, 2023).

This study extends this recent literature by focusing on the causal question of how WFH take-up affected worker mental health during and just after the strict lockdowns enacted in Australia, with the analysis time period extending from 2020 to 2022. Australia provides an ideal context to examine the effects of WFH due to its more prolonged lockdown period and

high vaccination coverage compared to other high-income countries, resulting in a large-scale, three-phase WFH take-up 'quasi-experiment' over 2020-2022, with relatively low COVID-19 spread at the same time reducing confounding from the effects of infection (Kong & Lam, 2024).

As a result, this study also offers more generalisable insights on WFH arrangements than recent causal studies focusing only on the lockdown period. This study also analyses particularly detailed and information-rich panel data on nearly 5,500 continuously employed workers from the Household, Income and Panel Dynamics in Australia (HILDA) survey, which allows for more detailed identification of heterogenous mental health impacts by WFH intensity, job control, perceived social support, and worker demographics. Compared to other studies examining the effects of WFH in the field of organisational behaviour (Biron & Van Veldhoven, 2016; Lapierre et al., 2016), this study analyses a much larger, national-level representative survey sample of workers across all industries over a long time period.

Theoretical insights

Employment and worker mental health

Mental health is strongly interconnected with employment (Frijters et al., 2014), the nature of work and workplace characteristics (Productivity Commission, 2021). Poor mental health lowers the ability to be actively employed, leads to more sick days and lowers workplace productivity through 'presenteeism' (Frijters et al., 2014). Conversely, poor workplace practices and risk factors such as high job demands with little control, imbalance between effort and reward, and low organisational justice may create poor psychosocial work environments and worsen mental health (Milner et al., 2015; Productivity Commission, 2021).

Grossman model of health production

Under the Grossman microeconomic model of health production, good mental health is valued both as a "consumption" and an "investment" good (Grossman, 1972), that is, as something to be valued in its own right and because it enables participation in income-producing activities (Zweifel et al., 2009). An individual's production of mental health depends on inputs of market goods (such as medical care, housing, and diet) and health-producing activities (such as exercise and recreation), subject to constraints of income and time and net of the ongoing depreciation of health stock over the life cycle (Grossman, 1972). The net addition to an individual's mental health stock depends on the marginal productivity of these inputs.

In this framework, WFH would contribute to better mental health if it freed up time previously spent commuting or engaging in workplace socialising and enables more investment in health-producing activities such as medical care, exercise, recreation, or improved work-life balance (Sturges, 2012), without compromising the use of that good health in income production. Conversely, mental health would worsen if WFH reduced opportunities to engage in effective health-producing activities, if health-promoting practices available at work (such as peer support) were displaced by health-harming practices at home (such as isolation or overwork), or if the ability to perform work and generate income were undermined.

This model may also help explain why the mental health effects of WFH during and after lockdowns may vary across workers. For instance, workers with low perceived control over tasks or schedules may be unable to convert the extra time or flexibility from WFH into health-producing activities. Similarly, while social support is often protective of mental

health (Cohen & Wills, 1985), its buffering role may have been constrained during lockdowns when physical interactions were restricted, limiting its marginal productivity.

For women, and particularly those with dependent children, dual work, WFH with caregiving and homeschooling responsibilities (Dunatchik et al., 2021; Shumate & Fulk, 2004) may have crowded out time for self-care, reducing the net mental health benefits of WFH despite increased flexibility. The intensity of home working may also matter. While moderate exposure to WFH may provide sufficient flexibility to improve health, high-intensity exposure particularly during lockdowns, may have displaced health-promoting activities, amplified stressors or resulted in the exertion of additional effort (Kelliher & Anderson, 2010) .

Psychological science theories

The impact of WFH on mental health during and after lockdowns can also be understood through the lens of several psychological science frameworks. The transactional model of stress suggests (Lazarus, 1984) that stress arises when individuals appraise external demands as exceeding their available 'resources', and then select coping strategies in response. In the WFH context, lockdowns, infection spread, blurred work–life boundaries and technological demands may have heightened perceived strain, while personal coping resources such as routines, space, job control and flexibility may have shaped ultimate wellbeing outcomes.

The job demands-control model (Daniels & Guppy, 1994; Karasek Jr, 1979) further highlights that high job demands coupled with low autonomy may undermine wellbeing, whereas greater decision latitude can protect against the intensification of work pressures that often accompany WFH. Finally, the social support and buffering hypothesis (Cohen & Wills, 1985) emphasises the role of communication and instrumental help in buffering the effect of stressors on wellbeing. During lockdowns, reduced in-person contact may have amplified

risks to mental health, yet ongoing social exchanges, whether virtual or within households, could buffer some of these effects. Overall, these perspectives suggest that the mental health impacts of WFH may depend not only on workload and job design but also on how workers appraise new demands, the degree of job control they retain, and the availability of social support during periods of disruption and transition.

Related literature

Empirical evidence on whether WFH is beneficial or harmful to mental health has been mixed in the past (Lunde et al., 2022; Oakman et al., 2020), due to the use of various identification strategies and worker samples used to isolate impacts (Anderson et al., 2015; Butler et al., 2009; Kazekami, 2020; Shepherd-Banigan et al., 2016; Song & Gao, 2020). Recent studies have focused specifically on lockdown years, which limits generalisability outside of this unique context (Bertoni et al., 2025; Gueguen & Senik, 2023; Niebuhr et al., 2022; Schifano et al., 2021; Somasundram et al., 2022).

Many pre-pandemic studies suffer from methodological limitations, and some are also not generalisable due to a focus on specific worker types and industries (Anderson et al., 2015; Butler et al., 2009; Kitagawa et al., 2021). The primary challenge in identifying the health impacts of working from home is endogeneity and reverse causation. Certain workers, such as those experiencing worse mental health (McDowell & Fossey, 2015) or those experiencing mental health-impacting life events such as childbirth (Boden Jr, 1999) may ‘select into’ spending more time working at home. Furthermore, people working from home differ substantially from those who do not work from home on many observable and unobservable characteristics, which may create selectivity bias, if these characteristics are not adequately controlled for.

Several past studies analysing associations between working from home and mental health use cross-sectional datasets and do not employ causal research designs or attempt to control for endogeneity or selectivity bias (Butler et al., 2009; Hokke et al., 2021; Niebuhr et al., 2022). Hence, the results in these past studies (Oakman et al., 2020) are likely to be confounded. While some past studies use panel data to analyse within-individual changes in mental health (Anderson et al., 2015; Kazekami, 2020; Shepherd-Banigan et al., 2016; Song & Gao, 2020), these methods only assist in controlling for potential heterogeneity bias from time-constant, individual level unobservables, but do not address potential endogeneity from time-varying unobservables.

Several pre-pandemic studies suggest that working from home may hold mental health benefits for particular worker groups including employed parents (Hokke et al., 2021; Shepherd-Banigan et al., 2016), government employees (Anderson et al., 2015) and employees of large companies (Butler et al., 2009). However, some studies find WFH to be associated with increased stress (Kazekami, 2020), exhaustion (Windeler et al., 2017) and reduced happiness (Song & Gao, 2020).

Findings from recent studies analysing the impact of WFH on mental health (Niebuhr et al., 2022), including ones with more causal designs are specifically from the lockdown period (Bertoni et al., 2025; Gueguen & Senik, 2023). While these causal findings are more robust than earlier studies, they are more difficult to generalise outside of the strict lockdown period where most WFH was ‘mandated’ or ‘forced’. These factors may have diluted the pure ‘work from home’ impact on mental health. Nonetheless, the consensus amongst these recent studies is that WFH harmed mental health during the lockdowns (Bertoni et al., 2025; Gueguen & Senik, 2023; Niebuhr et al., 2022; Oakman et al., 2022; Schifano et al., 2021; Somasundram et al., 2022)..

Institutional context: the pandemic, lockdowns and the WFH 'experiment' in Australia

Australia recorded its first case of coronavirus disease 2019 (COVID-19), caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), in late January of 2020. The subsequent growth of COVID-19 cases led to the Government implementing a series of public health measures to contain spread. This included restrictions ('lockdown measures') on domestic and international travel, the suspension or closure of non-essential businesses and activities, 'stay at home' orders where people could only leave their homes for essential reasons (such as essential contact work and grocery shopping), social distancing rules, quarantine periods for people exposed to COVID-19, and a shift to remote schooling and WFH arrangements (Reserve Bank of Australia, 2025).

Australians subsequently experienced several lockdown periods over 2020 and 2021, including a national lockdown lasting six weeks in March 2020 and shorter and more targeted lockdowns imposed by State and Territory Governments from mid-2020 to manage local outbreaks of the virus in their jurisdictions (Reserve Bank of Australia, 2025).

Most notable in 2020 was strict lockdown imposed in Melbourne, the capital city of the jurisdiction of Victoria which contains a quarter of the national population (Stobart & Duckett, 2022). The second COVID-19 wave in Victoria was much bigger than the first, with more community spread, resulting in a strict and long lockdown in Victoria including school and childcare closures, business-wide and retail shutdowns, limited numbers permitted to work in certain industries, take-away only at cafes and restaurants and people being required to stay home unless exercising or shopping. Moreover, exercise was limited to one hour a day, shopping was limited to one person per household per day, masks were mandatory indoors and outdoors, and travel was restricted to a 5 km radius with a night-time curfew (no-

one allowed outside past 8pm) (Stobart & Duckett, 2022). Melbourne ultimately spent 262 days in lockdown (Macreadie, 2022) which included WFH restrictions.

Outbreaks of Delta variants in mid-2021 led to the reintroduction of lockdowns including WFH restrictions in New South Wales, Victoria and the Australian Capital Territory, with around half of the Australian population living under significant restrictions in the September quarter of 2021 (Reserve Bank of Australia, 2025). While fewer restrictions followed the outbreak of Omicron in late 2021, the Reserve Bank of Australia (2025) notes that public mobility data showed declines over 2020 and 2021, as many people chose to take precautions, including working from home.

By December 2021, around 91% of the Australian population aged 16+ years old was fully vaccinated against COVID-19 (Australian Government, 2021). This set up the transition out of strict lockdown conditions and the end of pandemic 'norms', with individual jurisdictions revoking their pandemic-related public safety orders over 2022 (Department of Health Victoria, 2022; NSW Health, 2022).

This landscape resulted in what was effectively a three-phase "forced experiment" (quasi-experiment) in WFH (Productivity Commission, 2021) in Australia:

- Phase 1 (2020): Initial spread of COVID-19 cases resulting in unexpected lockdowns and take-up of WFH over 2020, particularly in Victoria;
- Phase 2 (2021)*:* The deepening of lockdowns nationally, across jurisdictions with further uptake of WFH; and
- Phase 3 (2022): A relaxing of lockdown restrictions with high vaccination rates, but a maintenance of WFH in less-harsh conditions.

As noted by the Reserve Bank of Australia (2023), the COVID-19 experiment had brought on a 'structural shift' with persistently reduced office attendance rates in major cities due to

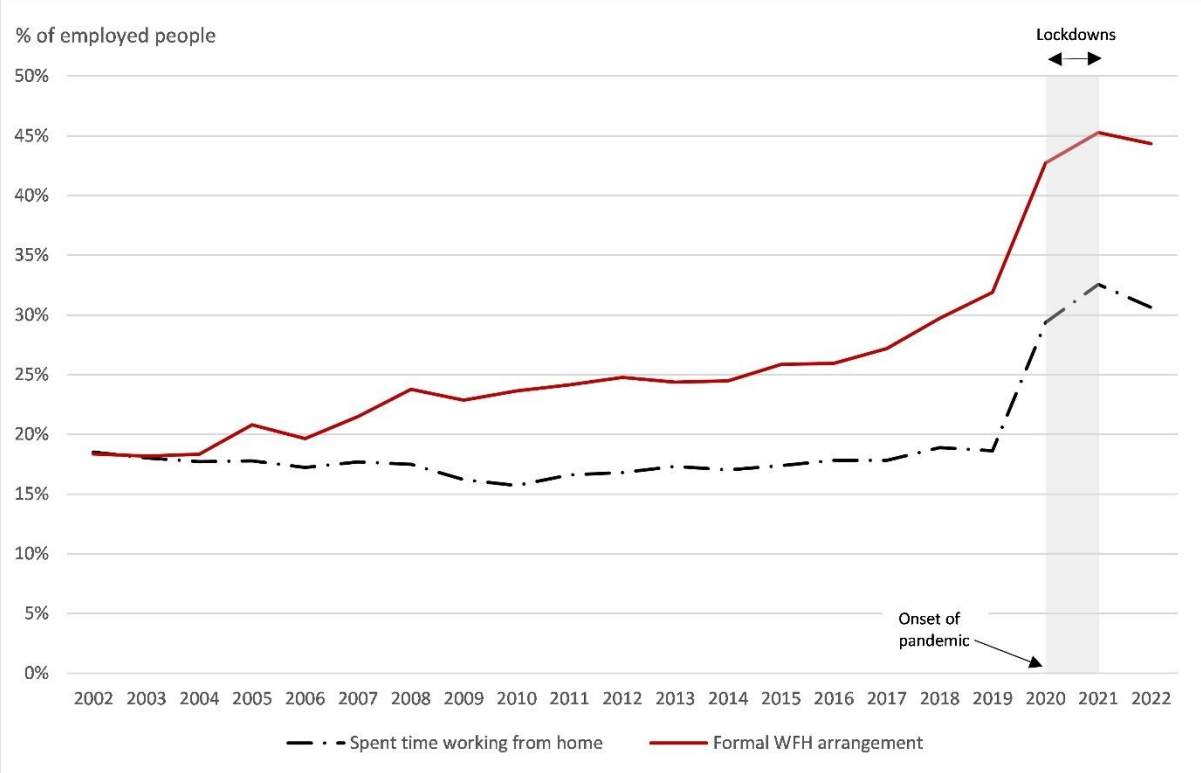
WFH. The immediate post-lockdown year, 2022, was close enough to the lockdowns to be considered an 'experimental' phase (without other harsh social restrictions). In more recent years, WFH has become subject to greater policy control by employers and autonomous choices by workers, reducing the ability to identify a causal effect (due to endogeneity).

For that reason, this study focuses on the impacts of the WFH 'experiment' in the years 2020-2022.

National survey data from Australian workers in **Figure 1** shows trends in the proportion of employed people who reported WFH over time in Australia including during the pandemic 'experiment' period. In pre-pandemic times (2002 to 2019), this proportion stayed relatively stable at around 16-19 per cent per cent of workers. The onset of the COVID-19 pandemic and lockdowns in 2020 resulted in a steep increase in this proportion to approximately 29 percent of all workers. This increased further in 2021 to nearly 33% as lockdowns deepened nationally, before dipping back to around 30% again in the post-lockdown year, 2022.

Figure 1 also shows the pandemic and related lockdowns triggered changes on the employer side, with a similar spike and maintained increase in the proportion of employees reporting that they had access to formal WFH arrangements from their employer.

Figure 1: Employed people who worked from home or who reported they (or their peers) had access to WFH arrangements from their employer over time (%) (exc. self-employed)



Source: Author's calculations using Household, Income, and Labour Dynamics in Australia (HILDA) data restricted release 22 (Melbourne Institute, 2023)

Data, variables, and methods

Data

This study analysed an unbalanced panel of employed individuals from the Household, Income and Labour Dynamics in Australia (HILDA) survey, a household-based panel study conducted annually since 2001, with the first wave contained information on 7,682 responding households and 19,914 persons. The sample was replenished in Wave 11 with an additional 2,153 households. The first 'pandemic wave', Wave 20, contained information on 7,552 responding households and a total of 18,160 persons, with data collection taking place during from August 2020 onwards (Summerfield, 2021).

To conduct the estimations, the Waves 15-22 were used to ensure coverage of outcomes and trends before and after the WFH experimental period that started in 2020 (Melbourne Institute, 2023). The analysis in this study was limited to employees rather than self-employed individuals[2], to remove any effect of selection into self-employment, which encompasses greater autonomy and discretion to work from home. The sample selected, was continuously employed over 2019-2022, to avoid confounding from employment loss effects during the pandemic and limited to those aged 20 years or older in 2019 (to ensure focus on individuals of legal working in the earliest estimation year, 2015). This resulted in a sample size of nearly 5,500 workers (over 28,000 observations) across the estimations conducted.

Treatment: any time spent working from home

The key covariate of interest (the variable that defined 'treatment') in the analysis was whether any time was spent working at home. HILDA asked workers in every wave '*whether any of their usual working hours were worked at home'*. Using this survey question, a dummy variable (WFH_{it}) was created for each worker (i) in the sample in each wave (t) indicating whether this individual spent time working at home (where *1* = any time worked at home and *0* otherwise). Trends in this variable are plotted in **Figure 1** and previously discussed.

The HILDA survey also asked questions on how many weekly hours an individual usually worked and how many of these were worked at home. Using these survey questions, another categorical variable was constructed indicating four intensity groups for time spent WFH (for the heterogeneity analysis).

Mental health outcome variable: distribution and trends

The outcome variable in this analysis ($\mathrm{MH_{it}}$) was the five-item Mental Health Inventory (MHI-5), a validated subscale measure in the 36-item Short Form Survey (SF-36) included in HILDA. The

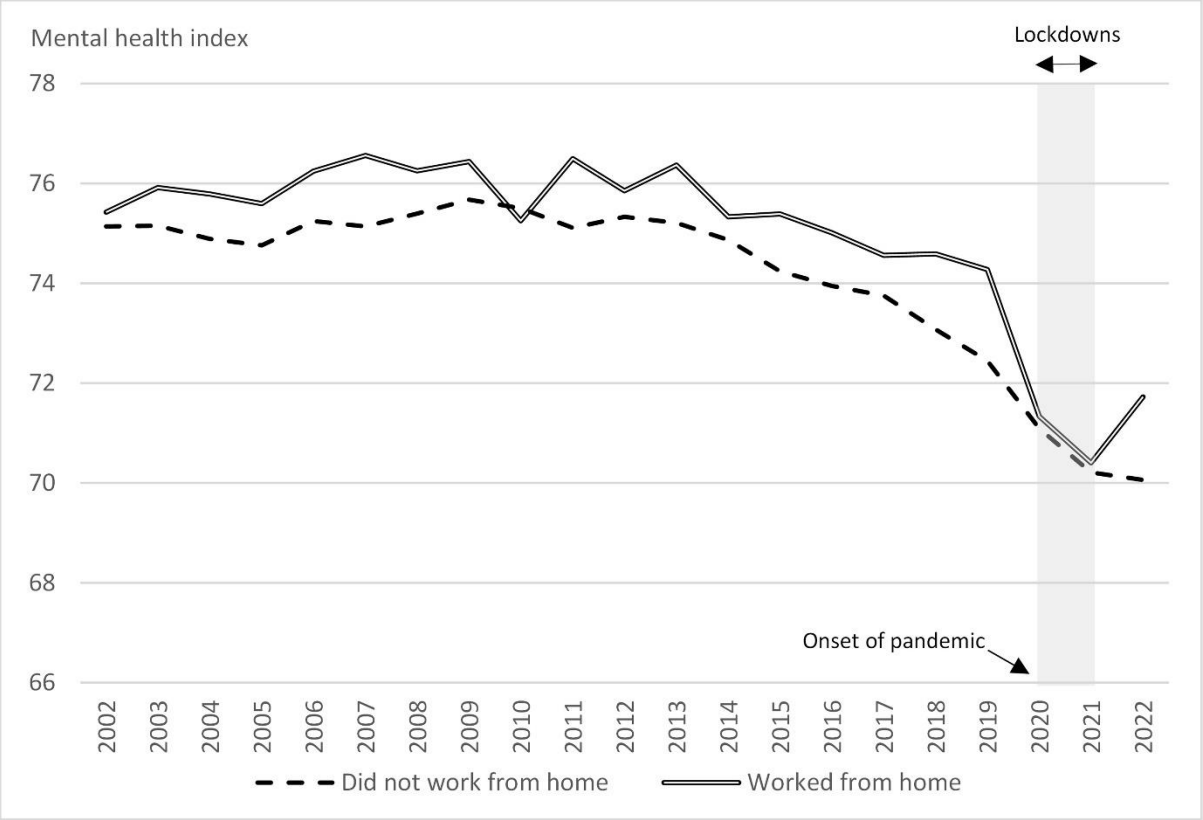
SF-36 is one of the most widely used self-completion measures of health status (Butterworth & Crosier, 2004), and has been widely used for population and clinical research in Australia and for screening psychiatric disorders internationally (Butterworth & Crosier, 2004; Marosszeky & Sansoni, 2005; Ware et al., 2001). The five items included in MHI-5 assess the frequency of anxiety and mood symptoms of participants over a retrospective four-week period. Scores on each item are summed, and scale values are transformed to range from 0 to 100, with higher values indicating better mental health, and vice versa (Butterworth et al., 2022).

Figure 2 shows the trends the average MHI-5 for Australian workers (excluding self-employed) in the HILDA dataset over time, including those who worked from home and those who did not. The general trend is declining mental health for all workers from 2011 onwards, with relatively similar average scores between those who worked from home and those who did not.

These mental health trajectories seemed to have evolved roughly in parallel to each other prior to the COVID-19 pandemic. While self-reported average mental health continued to deteriorate for both worker types after the onset of the pandemic and during the lockdowns, a much steeper decline is observed for those who worked from home relative to those who did not, with the gap in scores between the two groups narrowing during lockdowns.

Interestingly, in the immediate post-lockdown year, 2022, average mental health appears to have rebounded (improved) for WFH workers, up to a continuation of its pre-pandemic trends.

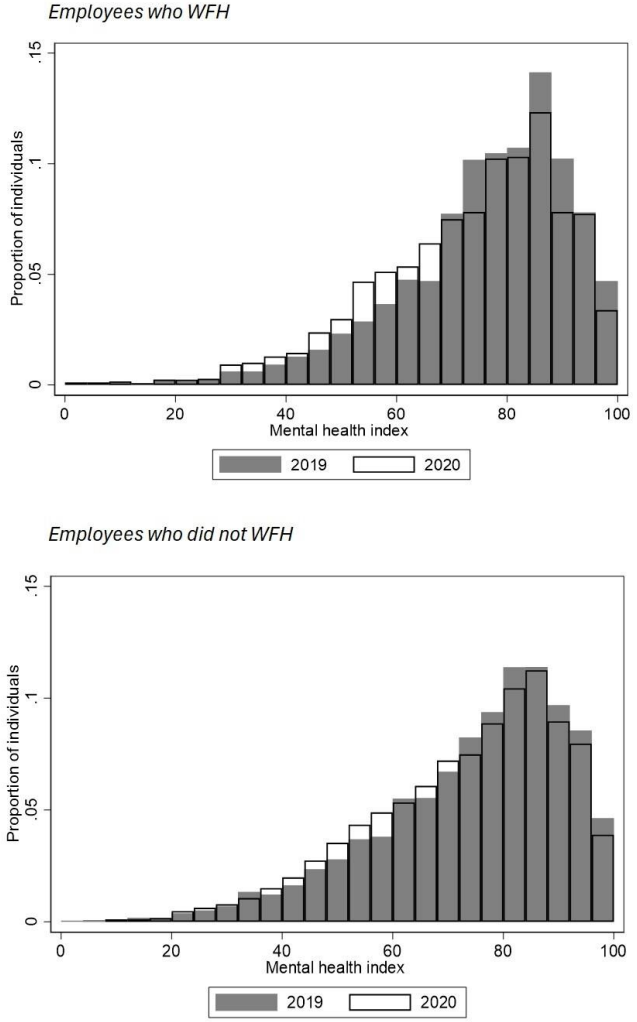
Figure 2: Mean Mental Health Inventory scores for employed people over time



Source: Author's calculations using HILDA data restricted release 22 (Melbourne Institute, 2023).

A similar story is apparent when we look at the shift in the distributions of MHI-5 scores for those who worked from home and those did not over 2019 and 2020 in HILDA in **Figure 3**. While the distributions for both worker types shifted left from 2019 to 2020 (the onset of the pandemic), representing a deterioration in mental health, a more pronounced shift is seen for those who worked from home.

Figure 3: Distribution of Mental Health Inventory-5 scores for work from home and non-work from home employees (waves 19 and 20)



Source: Author's calculations using HILDA data restricted release 22 (Melbourne Institute, 2023).

Descriptive statistics for estimation sample: treatment and control groups

Basic descriptive statistics for the estimation sample in Wave 19 (i.e. 2019, the immediate pre-pandemic wave) are presented in **Table 1**, including demographic and work-related characteristics. Several differences in observable characteristics are apparent between the WFH treatment group, and non-WFH control group in 2019, including level of educational attainment and occupation and industry mix. These observable differences are expected given the differing levels of tele-workability across occupations and industries (Bertoni et al., 2025).

While these descriptive statistics indicate show differences in averages ('levels') between the treatment and control groups, the difference-in-differences identification strategy chosen in this study to estimate effects (detailed in the next section), relies on parallel trends in outcomes rather than balance on observable characteristics (Angrist & Pischke, 2009).

Table 1: Descriptive statistics, treated (WFH=1) and control (WFH=0) groups in 2019

Variable (type)	*Treatment group (WFH=1)*			*Control group (WFH=0)*		
	N	***average***	***std. dev***	***N***	***average***	***std. dev***
Age (years)	1,209	42.53	11.12	3,767	41.03	12.82
Female (0/1)	1,209	0.54	0.50	3,767	0.49	0.50
Married / de-facto (0/1)	1,209	0.81	0.39	3,767	0.70	0.46
Dep. children aged<10 (0/1)	1,209	0.46	0.50	3,767	0.36	0.48
Older dep. children (0/1)	1,209	0.16	0.37	3,767	0.12	0.32
Highest education (0/1):						
Certificate / Diploma	1,209	0.23	0.42	3,767	0.40	0.49
University degree	1,209	0.64	0.48	3,767	0.30	0.46
High school or less	1,209	0.13	0.34	3,767	0.30	0.46
Occupation type (0/1):						
Managers	1,209	0.26	0.44	3,767	0.10	0.30
Professionals	1,209	0.52	0.50	3,767	0.22	0.41
Technicians and trades	1,209	0.04	0.19	3,767	0.14	0.35
Community/personal service	1,209	0.04	0.20	3,767	0.15	0.35
Sales	1,209	0.03	0.17	3,767	0.08	0.27
Clerical and administrative	1,209	0.10	0.30	3,767	0.14	0.34
Machine operators/labourers	1,209	0.01	0.12	3,767	0.18	0.39
Industry (0/1)						
Agriculture, forestry, fishing	1,209	0.01	0.08	3,767	0.02	0.14
Mining	1,209	0.02	0.12	3,767	0.03	0.16
Manufacturing	1,209	0.06	0.24	3,767	0.10	0.30
Electricity/gas/water	1,209	0.01	0.11	3,767	0.01	0.08
Construction	1,209	0.03	0.18	3,767	0.07	0.25
Wholesale trade	1,209	0.03	0.17	3,767	0.03	0.17
Retail trade	1,209	0.03	0.18	3,767	0.12	0.33
Restaurants and hotels	1,209	0.01	0.09	3,767	0.04	0.19
Finance and insurance	1,209	0.07	0.26	3,767	0.02	0.14
Transport and storage	1,209	0.02	0.15	3,767	0.05	0.22
Communication and services	1,209	0.02	0.13	3,767	0.01	0.10
Culture & recreation	1,209	0.03	0.16	3,767	0.02	0.15
Other services	1,209	0.16	0.37	3,767	0.09	0.28
Health	1,209	0.10	0.29	3,767	0.24	0.43
Education	1,209	0.28	0.45	3,767	0.09	0.28
Government admin	1,209	0.09	0.29	3,767	0.07	0.26
Other / missing	1,209	0.03	0.16	3,767	0.01	0.09

Heterogeneity analysis variables

As discussed in the *Theoretical Insights* section, the mental health impact of WFH on worker mental health may have been moderated by several worker and job-related characteristics. Heterogeneity was examined across the following characteristics of interest, which were modelled as a series of dummy variables for each characteristic 'level':

- *Gender by dependent children (under the age of 10 years old):* males with no dependents, females with no dependents, males with dependents, females with dependents;
- *WFH 'intensity' (based on weekly hours, and self-reported hours WFH):* >0 but ≤25% of time, >25 but ≤50% of time, >50 but ≤75% of time, >75 but ≤100% of time;
- *Perceived social support:* low, medium, high; and
- *Perceived job control:* low, medium, high.

These last two variables were created based on past literature analysing job control and social support using HILDA data (Butterworth et al., 2010; Milner et al., 2016). Perceived job control in HILDA was assessed using three survey items on decision authority, each rated on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree): *'I have the freedom to decide how I do my own work'*, *'I have a lot to say about what happens on my job'*, and *'I have a lot of freedom to decide when I do my work'* (Butterworth et al., 2010). Responses across these items were averaged to create a composite job control score ranging from 1 to 7, with higher scores representing more job control and vice versa. Individuals were then grouped into three categories accordingly to their score: those in the lowest quartile were coded as having low job control, those between the 25th and 50th percentiles as medium job control, and those above the 50th percentile as high job control.

Similarly, a composite social support score was constructed from ten 7-point Likert scale survey items in HILDA: *'I have no one to lean on in times of trouble'* (reverse coded), *'I often feel very lonely'* (reverse coded), '*I enjoy the time I spend with the people that are important to me*', *'I seem to have a lot of friends'*, '*People don't come and visit as much as I would like'* (reverse coded), *'I often need help from other people but can't get it'* (reverse coded), *'I don't have anyone that I can confide in'* (reverse coded*), 'There is someone who can always cheer me up when I am down', 'When I need someone to help me out, I can usually find someone*' and *'When something's on my mind, just talking with the people I know can make me feel better'*. Individuals were categorised into low, medium, and high social support using percentile cut-offs consistent with those applied to the job control measure (Milner et al., 2016).

Identification strategy

Baseline estimation

To estimate the impact of working from home (WFH) on worker mental health, a difference-in-differences (DID) approach was employed in this study. This technique of causal inference is widely used in economics and social sciences to infer causal effects when a 'purely randomised' policy experiment is not available (Angrist & Pischke, 2009).

The DID approach estimates causal effects by comparing how outcomes change over time for a treatment group (in this case, workers who worked from home) relative to a control group (workers who continued working on-site). Its validity rests on the parallel trends assumption, which holds that, in the absence of the WFH "experiment" created by Australia's lockdowns, mental health outcomes for both groups would have followed similar trajectories. Although this assumption cannot be definitively proven, researchers can build confidence by examining pre-treatment outcome trends. Visual and statistical checks of mental health patterns prior to

the pandemic provide such evidence. As shown in **Figure 2**, mental health outcomes for both groups evolved along broadly parallel paths before the onset of the 2020–2021 lockdowns.

To estimate the impact of WFH on worker mental health, this study adopted a regression specification similar to that used by Schurer et al. (2023) in their analysis of the effects of the Melbourne lockdowns on behavioural and lifestyle outcomes. The estimation equation was:

$$\mathrm{MH_{it}} = \alpha_1 + \beta_1 WFH_{it} + \gamma_1 Year_t + \delta_1 (WFH_{it} \times Year_t) + \mu_i + \varepsilon_{it} \quad \ldots (1)$$

Here the outcome $\mathrm{MH_{it}}$ was the self-reported mental health (MHI-5 score) of worker *i* HILDA survey year *t*. This was regressed on a flexible, binary treatment group indicator (WFH_{it}), which indicated whether individual *i* spent any time working from home in year *t*. Year dummies ($Year_t$) captured the pre-pandemic survey years (2015–2018, with 2019 as the omitted base year) and one of the "WFH experiment" years: either 2020, 2021, or 2022. The coefficient of interest, δ_1, was attached to the interaction between working from home and each experiment year. This captured the DID estimate of how WFH affected mental health in each year relative to the baseline pre-pandemic year of 2019. The term μ_i captured individual-specific, time-invariant factors that may have influenced reported mental health (for example, stable reporting tendencies), while ε_{it} represents the error term.

The causal effect was therefore identified in equation (1) when the interaction term combined WFH participation with one of the 'experiment' years (2020, 2021, or 2022). Furthermore, this interaction term combined with the pre-WFH experiment years (2015-2018) offers a statistical check for the parallel trends assumption (supported if coefficients on these are insignificant).

The effect on mental health in each experiment WFH year was estimated in a separate model rather than in a single specification, because the nature of WFH 'treatment' differed across the three phases from 2020-2022 (as described in the *Institutional context* section*)*. Treating

these years as distinct "experiments" allowed the analysis to identify effects within their specific contexts, rather than assuming a uniform impact of WFH across all three years.

Including covariates in DID models imposes additional assumptions, beyond parallel trends, which may not hold in practice and can undermine causal identification (Baker et al., 2025). In line with this, covariates were not added to the baseline DID model to avoid such biases and preserve a clean comparison under the standard parallel trends framework.

In all the models, standard errors were clustered at the occupation by industry level, to reflect that WFH treatment in the experiment / lockdown years was based on the level of tele-workability of worker's job type and industry at the time. This resulted in over 350 clusters.

Heterogeneity analyses

A series of heterogeneity analyses were conducted within the DID format to examine whether mental health impacts were moderated by several worker and job-related factors discussed in the *Theoretical Insights* section. These were conducted by including characteristics of interest variables (dummies for each level), C_{it}, in equation (1), along interactions between these and the $WFH_{it} \times Year_t$ interaction term for the treatment years (2020, 2021 and 2022).

Estimation results

Baseline results

The baseline DID results presented in **Table 2** show that WFH led to statistically significant yet modest deteriorations in mental health, on average, during the lockdown years of 2020 and 2021 (-1.01 MHI-5 points in 2020 and -1.1 MHI-5 points in 2021, $p<0.5$).

An insignificant effect was estimated for the post-lockdown year, 2022, suggesting no evidence of harm or benefit to mental health from WFH, on average, in the absence of lockdowns. The magnitude of the declines in 2020 and 2021 is relatively small, equivalent to

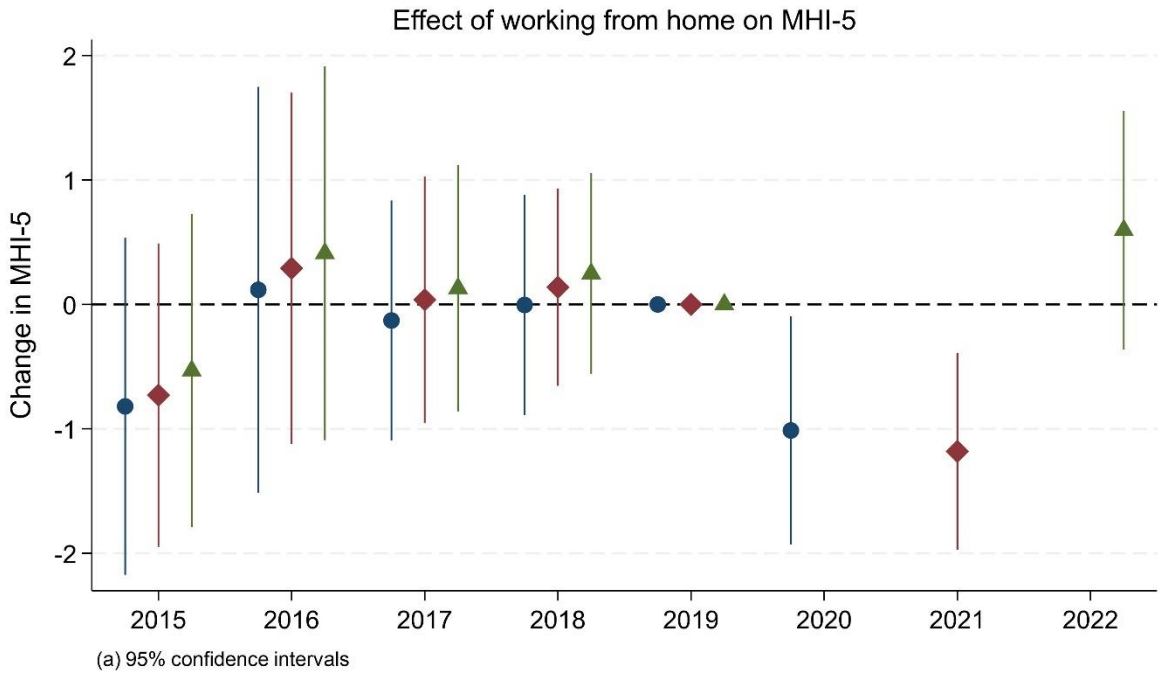
0.06-0.07 standard deviations. **Figure 4** shows the DID estimated effect sizes in each year in an event-study visualisation, along with confidence intervals (with separate models for 2020, 2021 and 2022). The estimated pre-2020 effects were insignificant, offering some statistical support for the parallel trends assumption.

Table 2: DID-estimated effects of WFH on mental health in 2020-2022 (MHI-5)

	2020 (Model 1)			2021 (Model 2)			2022 (Model 3)		
	Coeff	**S.E**	**P**	**Coeff**	**S.E**	**P**	**Coeff**	**S.E**	**P**
Estimate	-1.013**	0.467	0.031	-1.181***	0.403	0.004	0.596	0.487	0.222
N (individuals)	*28,112 (5,465)*			*28,091 (5,466)*			*28,032 (5,460)*		

Standard errors clustered at the occupation-industry group level. *p<0.1*, p<0.05**, p<0.01****

Figure 4: Difference-in-difference estimated effects of working from home on mental health by year (event study chart)



Heterogeneity analyses

The results of the heterogeneity analyses by gender and dependent group, WFH intensity, social support and job support groups are presented in **Table 3**, with estimates and 95% confidence intervals visually plotted in **Figure 5** to **Figure 8**.

For WFH intensity, those working 75–100% of hours from home (high intensity WFH) experienced significant declines in mental health in the initial lockdown year 2020 (–1.96 MHI-5 points, $p<0.05$), but this effect was not significant in 2021. By contrast, in 2021, negative mental health effects were concentrated among those working 0–25% of their hours from home (–1.93 MHI-5 points, $p<0.01$). In 2022, in alignment with the baseline DID results, most intensity groups had insignificant mental health effects from WFH. However, the 25–50% WFH group showed a positive and significant effect on mental health (+2.24 MHI-5 points, $p<0.01$).

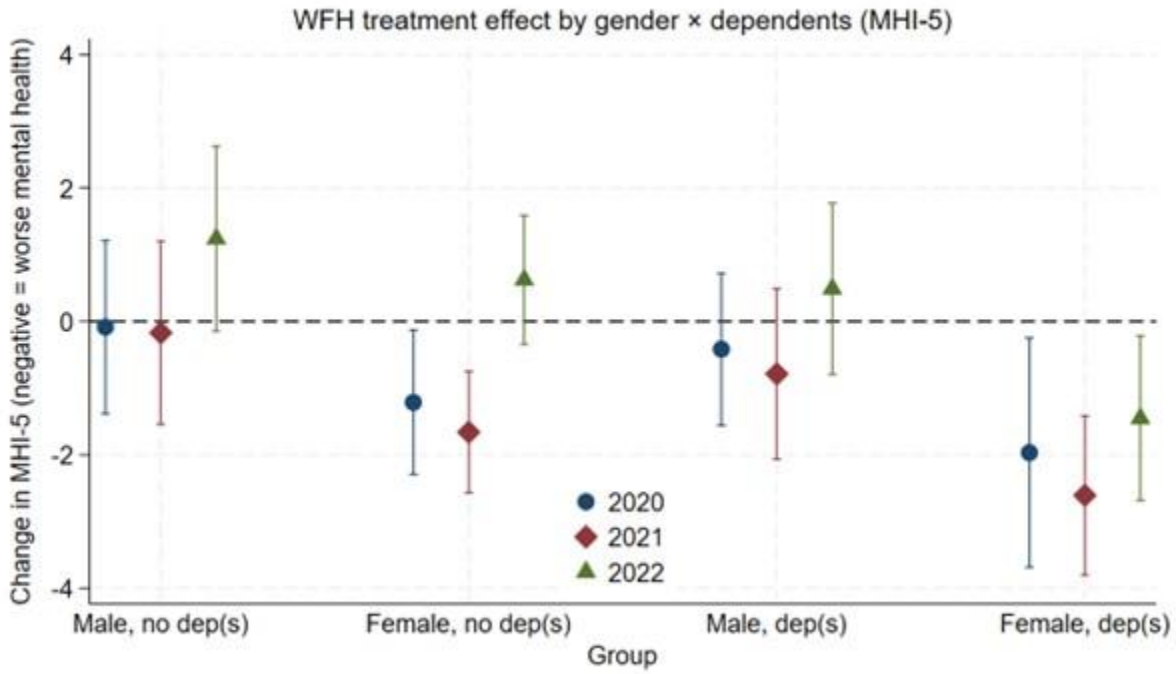
Gender-by-dependent status results show consistent negative effects for females, particularly those with dependent children. Female workers without dependents reported significant declines in 2020 (–1.22 MHI-5 points, $p<0.05$) and 2021 (–1.66 MHI-5 points, $p<0.01$), while females with dependents experienced larger and more persistent declines across all three years (–1.97 MHI-5 points in 2020, –2.61 in 2021, and –1.45 in 2022; $p<0.05$). In contrast, no significant mental health effects were observed for men, regardless of dependent status, although there is suggestive evidence of a positive effect for men without dependents in 2022 ($p<0.1$).

For social support, significant negative effects were evident among both high-support and low-support workers in 2020 (–1.22 and –1.38 MHI-5 points, respectively) and persisted into 2021 (–1.09 for high support, –1.66 for low support). However, these faded out in the post-

lockdown year, 2022. Workers with medium levels of social support showed no significant effects in any year.

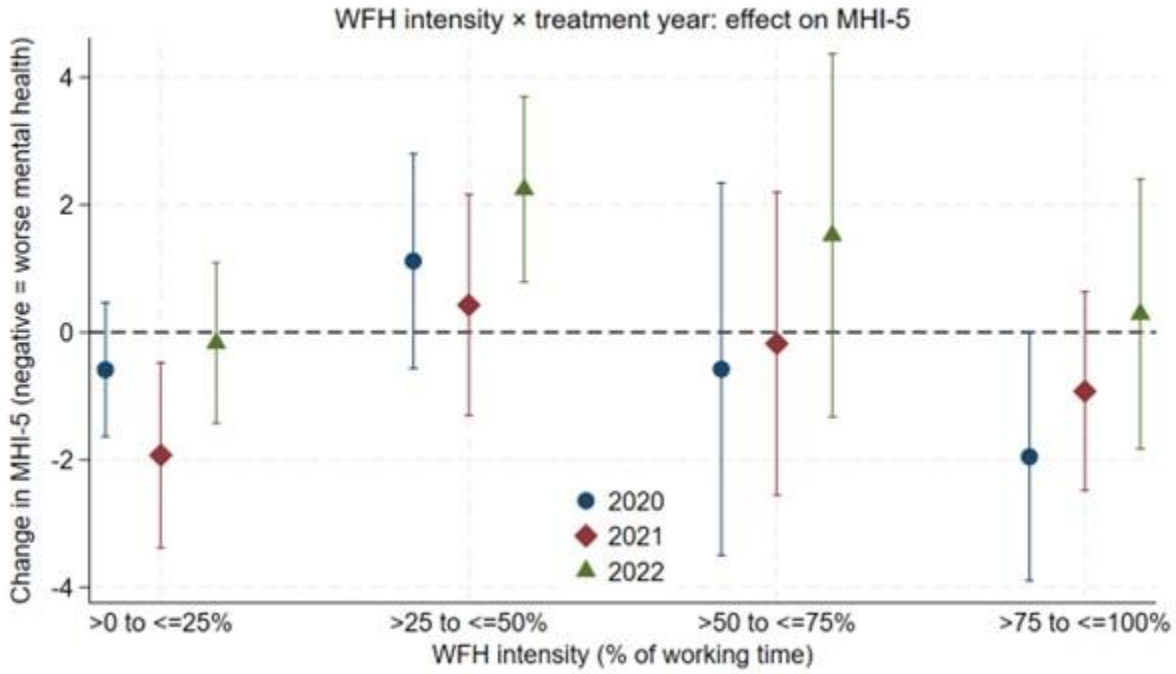
Finally, job control results reveal a clear gradient. In the lockdown years, 2020 and 2021, significant declines in mental health were observed across all groups, with the largest effects among workers with low job control (–2.29 MHI-5 points in 2020, –2.79 in 2021). In the post-lockdown year, 2022, the low job control group continued to exhibit significant negative effects of WFH on mental health (–2.40, $p<0.01$), while those with medium or high control showed no differences relative to pre-pandemic levels.

Figure 5: Difference-in-differences estimated effect of working from home on mental health – gender by dependent group



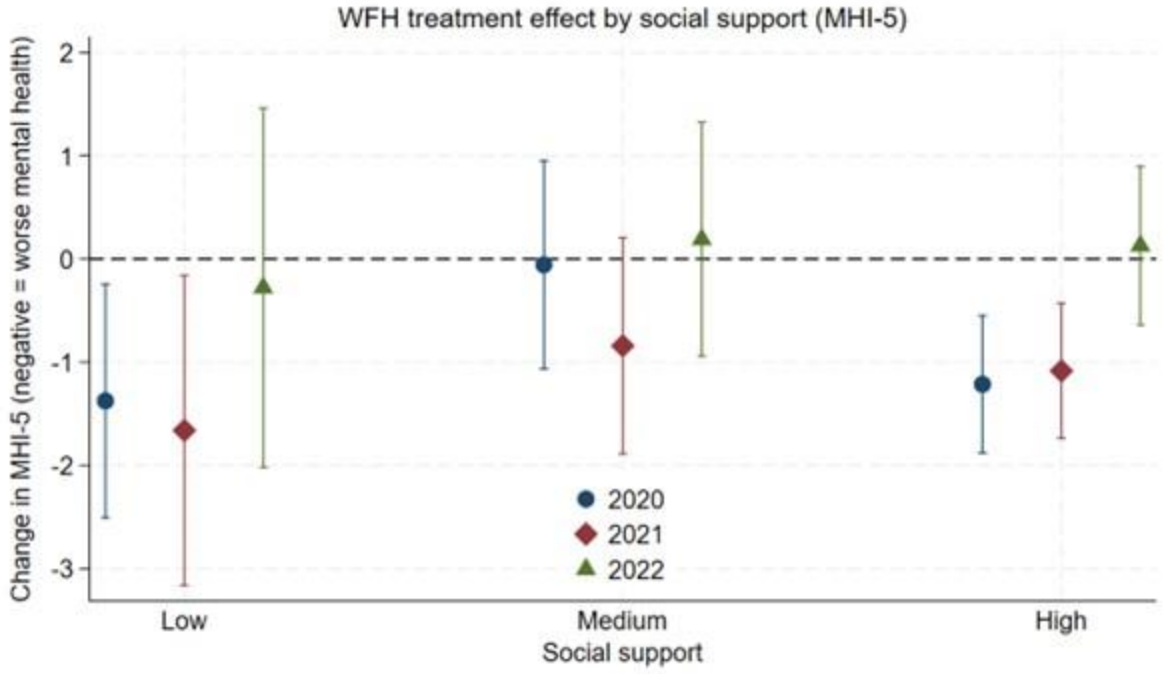
95% confidence intervals shown

Figure 6: Difference-in-differences estimated effect of working from home on mental health – work from home intensity group



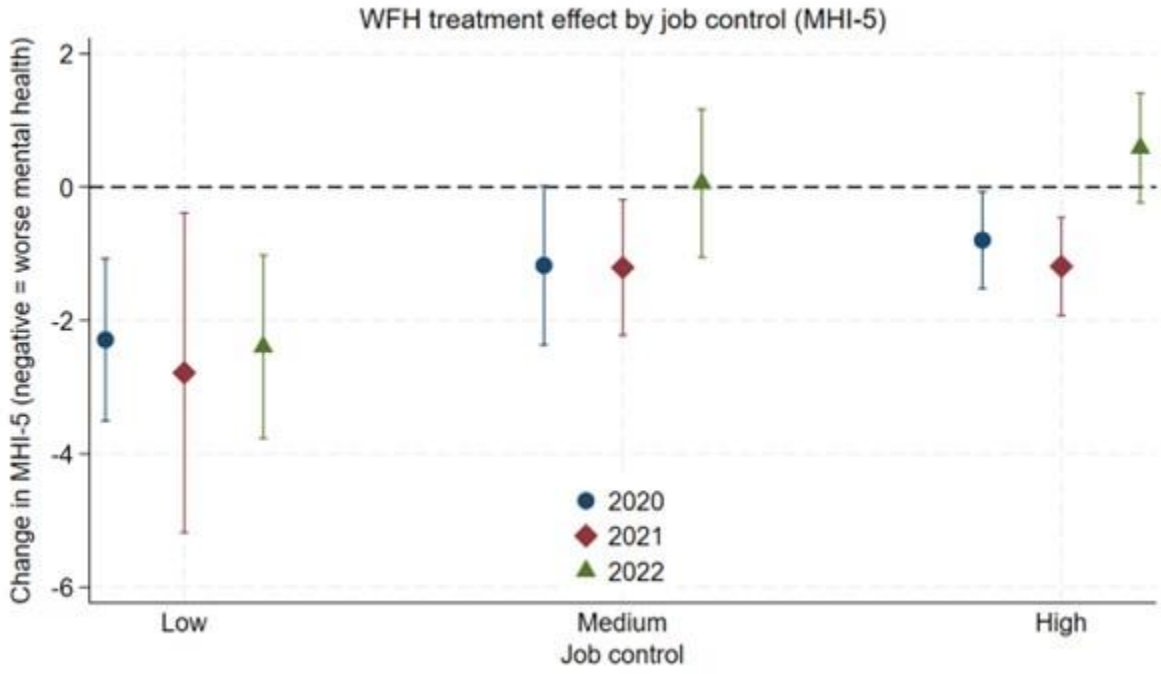
95% confidence intervals shown

Figure 7: Difference-in-differences estimated effect of working from home on mental health – social support level



95% confidence intervals shown

Figure 8: Difference-in-differences estimated effect of working from home on mental health – job control level



95% confidence intervals shown

Table 3: Heterogeneity analyses - Effects of WFH on mental health (MHI-5) within subgroups

	2020 (Model 1)			2021 (Model 2)			2022 (Model 3)		
	Coeff	**S.E**	**P**	**Coeff**	**S.E**	**P**	**Coeff**	**S.E**	**P**
WFH intensity (% hours)									
>0%, ≤25%	-0.590	0.537	0.272	-1.931***	0.739	0.009	-0.172	0.644	0.790
>25%, ≤50%	1.116	0.859	0.195	0.424	0.885	0.632	2.241***	0.742	0.003
>50%, ≤75%	-0.582	1.489	0.696	-0.1797	1.213	0.882	1.518	1.454	0.297
>75%, ≤100%	-1.957**	0.992	0.049	-0.929	0.795	0.243	0.287	1.079	0.791
N (individuals)	*28,112 (5,465)*			*28,091 (5,466)*			*28,032 (5,460)*		
Gender x Dependent(s)									
Male, no dep(s)	-0.086	0.662	0.897	-0.171	0.702	0.808	1.241*	0.708	0.080
Female, no dep(s)	-1.215**	0.553	0.029	-1.661***	0.463	0.000	0.625	0.494	0.206
Male, dep(s)	-0.417	0.581	0.473	-0.787	0.653	0.229	0.490	0.655	0.455
Female, dep(s)	-1.969**	0.877	0.025	-2.609***	0.609	0.000	-1.453**	0.628	0.021
N (individuals)	*28,112 (5,465)*			*28,091 (5,466)*			*28,032 (5,460)*		
Social support									
High	-1.215***	0.340	0.000	-1.085***	0.334	0.001	-0.278	0.888	0.754
Medium	-0.056	0.515	0.913	-0.842	0.535	0.116	0.191	0.579	0.741
Low	-1.376**	0.577	0.018	-1.662***	0.765	0.031	0.130	0.392	0.741
N (individuals)	*27,760 (5,458)*			*27,708 (5,453)*			*27,655 (5,448)*		
Job control									
High	-0.795**	0.371	0.030	-1.190***	0.375	0.002	0.587	0.418	0.161
Medium	-1.175*	0.609	0.054	-1.207**	0.520	0.021	0.059	0.567	0.918
Low	-2.290***	0.621	0.000	-2.786**	1.222	0.023	-2.397***	0.702	0.001
N (individuals)	*27,589 (5,437)*			*27,566 (5,438)*			*27,492 (5,427)*		

Standard errors clustered at the occupation-industry group level. *p<0.1*, p<0.05**, p<0.01****

Discussion and conclusions

This study provides new evidence on how WFH during and just after the COVID-19 lockdowns shaped worker mental health across different phases and groups. While concerns at the time suggested that WFH would trigger a "mental health crisis," the analysis here, using detailed worker panel data from Australia's 'WFH experiment', indicates that average self-reported mental health declined modestly during the lockdown years of 2020 and 2021. By 2022, there was no evidence of either improvement or deterioration in mental health from WFH on average.

These findings suggest that the "mental health crisis" narrative applied more to involuntary WFH under lockdown conditions than to WFH itself. They align with recent Australian evidence that the Victorian lockdown was responsible for small but significant declines in self-reported mental health in 2020 (Butterworth et al., 2022). It is also important to note that the average declines from WFH during the lockdown years were modest and did not reach clinical relevance (greater than 4 MHI-5 points) (Butterworth et al., 2022; Contopoulos-Ioannidis et al., 2009). Overall, the baseline results support policies that maintain access to hybrid work without fear of a generalised mental health crisis.

The heterogeneity analyses indicate that the mental health effects of WFH were not uniform across worker groups. In 2020, those WFH at high intensity (75–100% of hours) had the largest declines, reflecting the abrupt and isolating nature of mandated remote work, particularly during the Victorian lockdown. By contrast, in 2021 when restrictions deepened nationally, the largest negative effects were for those working predominantly on-site (0–25% of hours WFH). This may reflect stress due to heightened exposure risks and limited autonomy for this group, while many high-intensity WFH workers had by then adapted to remote work conditions. In 2022, after the end of lockdowns, results suggest positive effects

for hybrid work (25–50% of hours WFH). Together, these findings highlight how the effects of WFH intensity shifted with pandemic conditions, and that it was the lack of choice and heightened stressors in the lockdown context, rather than WFH itself, that drove mental health declines.

The gender-by-dependent status results illustrate that women, particularly those with dependent children, bore the brunt of worsened mental health due to WFH during the lockdown years. In the post lockdown year, 2022, women with dependent children continued to experience negative mental health impacts from WFH. These results are not surprising and align with other recent studies on WFH and lockdown effects on women (Bertoni et al., 2025; Butterworth et al., 2022; Gueguen & Senik, 2023; Schurer et al., 2023). Interestingly, the results also provide suggestive evidence of positive effects for men without dependent children in the post-lockdown year.

Further attention is warranted in exploring whether the negative WFH mental health effects for women with dependent children may relate to burden from dual caregiver/worker roles (Dunatchik et al., 2021), and whether WFH may reduce workplace visibility and hinder career progression for women[3]. Within this domain, gender-sensitive WFH policies such as enhancing childcare access, reducing stigma around workplace 'presence', and allowing for flexible timings and hours may help to reduce burdens and improve equity in outcomes.

Differences in mental health effects also emerged by levels of perceived job control and social support. During the lockdown years, negative mental health effects were present across the job control and social support spectrum, albeit with the largest impacts for those with low job control, suggesting limited buffering capacity of these resources (Daniels & Guppy, 1994; Karasek Jr, 1979) in the face of the lockdown-imposed stressors. By 2022, post-lockdowns, negative effects largely dissipated except for those in workers with low job control. This

suggests that job design and autonomy are important in designing future WFH policies that support mental wellbeing. In the 'new normal' of flexibility and remote work policies, employers may need to review job structures to avoid 'remote micromanagement' or rigid workflows that may harm worker wellbeing.

Overall, as WFH becomes embedded in labour markets across the world, policies should prioritise adequate supports for vulnerable groups, particularly working women balancing caregiving roles and workers in jobs with low perceived control, to ensure equitable mental wellbeing outcomes. The results support that hybrid arrangements, when carefully structured, may actually enhance the mental wellbeing of workers, if they allow workers to engage in effective health and income production (Grossman, 1972). Designing effective WFH policies will require balancing the reduction of work-family conflict (Lapierre et al., 2016) with the provision of flexibility, job and role quality, and autonomy with adequate recovery (Biron & Van Veldhoven, 2016), to reduce strain and promote sustainable wellbeing (Sanz-Vergel et al., 2011).

This study had some limitations. Both WFH and mental health are self-reported based on survey data, so results may reflect some reporting bias. The analysis also focused on workers who remained continuously employed, which means it did not capture the experiences of those who lost jobs or left the workforce during the pandemic. Hence, the effects should be interpreted as the mental health impact of WFH on workers with relatively stable employment trajectories. Finally, while the design isolated broad, population-level effects, it cannot fully reflect the diversity of individual circumstances, such as differences in occupations or local restrictions.

These caveats should be kept in mind, but they do not diminish the value of the findings in highlighting how the mental health effects of WFH shifted across different phases of the pandemic and were context-specific.

END NOTES

[1] Recent articles published through *Forbes* [available at: https://www.forbes.com/sites/bryanrobinson/2021/10/15/remote-workers-report-negative-mental-health-impacts-new-study-finds/?sh=e24582674b84] and the *BBC* [available at: https://www.bbc.com/worklife/article/20220616-is-remote-work-worse-for-wellbeing-than-people-think] raised concerns about the potential negative mental health impacts of remote work, based on recent cross-sectional surveys of remote workers.

[2] Defined as 'employee of own business', 'employer/self-employed' or 'unpaid family worker'.

[3] An article in the *Harvard Business Review* ('Why WFH Isn't Necessarily Good for Women') highlights several potential reasons why working from home may have adverse impacts on women's careers [available at: https://hbr.org/2020/07/why-wfh-isnt-necessarily-good-for-women].

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