HEDG

HEALTH, ECONOMETRICS AND DATA GROUP

THE UNIVERSITY of York

WP 23/03

Working from home and mental health: before and during the COVID-19 pandemic

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May 2023

http://www.york.ac.uk/economics/postgrad/herc/hedg/wps/

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Acknowledgements:

This study 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 and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this study, however, are those of the author and should not be attributed to either the Department of Social Services or the Melbourne Institute.

Conflict of interest: The author has no potential conflict of interest to declare.

Keywords: mental health, working from home, worker wellbeing, instrumental variable

JEL: D00, I18, J81

Abstract

Robust evidence on working from home and mental health is lacking, with recent concerns it may blur work-home boundaries. Working from home was discretionary and less intensive in pre-pandemic years, while during the pandemic, it was often intensive and 'mandated'. I estimate the relationship between working from home and mental health via fixed-effects and instrumental variable (IV) estimation. I find no evidence that working from home harmed mental health, on average, pre-pandemic, with IV estimates suggesting potentially improved health. Conversely, working from home may have deteriorated mental health during the pandemic, potentially due its 'forced', intensive nature during this time.

1 Introduction

The coronavirus (COVID-19) pandemic dramatically accelerated the take-up of working from home across all industries, largely due to public health mandates to reduce infection spread during 2020-2021. This large-scale 'mandated' take-up has, however, indirectly revealed the potential benefits and feasibility of remote work to both employers and workers, and encouraged some employers to adopt new technologies enabling remote work beyond the initial period of lockdowns and mandates (Productivity Commission, 2021).

Despite the rapidly changing nature of work and this shift towards flexibility, there is a paucity of robust empirical evidence on the mental health impacts that practices such as working from home have on workers (Lunde et al., 2022). Recently, concerns have been expressed around potential negative mental health effects due to the increased incidence of loneliness and isolation reported by remote workers[1].

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).

In this study, I focus on the question of whether working from home benefits or harms mental health. Under the Grossman model, good mental health is valued by an individual both as a 'consumption' and an 'investment' good (Grossman, 1972), that is, as something to be valued within itself, and because good mental health allows an individual to engage in income-producing activities (Zweifel et al., 2009). An individual's production of mental health is dependent on inputs of market goods (e.g. medical care, housing, diet) and health-producing activities (e.g. exercise, recreation), under the 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 the inputs used for health production.

Under this framework, working from home would contribute to better mental health if it freed up an individual's time (e.g. from commuting, socialising at work) to spend on effective, health-producing activities (e.g. seeking medical care, exercising, recreation and work/life balance through time spent with family), without compromising an individual's ability to use this good health for income production (e.g. through employment participation). Conversely, mental health would be adversely impacted if an individual was unable to engage in effective health-producing activities through working from home, if health-producing practices at work (e.g. socialising, colleague support) were displaced by health-harming practices at home (e.g. isolation, overwork), or if working from home adversely impacted an individual's ability to perform their work (i.e. engage in income production).

The existing empirical evidence on whether working from home is beneficial or harmful to mental health is mixed (Lunde et al., 2022; Oakman et al., 2020), due to the use of various identification strategies and worker samples to isolate impacts (Anderson et al., 2015; Butler et al., 2009; Kazekami, 2020; Shepherd-Banigan et al., 2016; Song & Gao, 2020), with recent studies focusing specifically on pandemic years, which limits generalisability (Bertoni et al., 2021; Niebuhr et al., 2022; Oakman et al., 2022; Schifano et al., 2021; Somasundram et al., 2022).

Many pre-pandemic studies suffer from methodological limitations, and some are 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 working from home 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 working from home on mental health (Niebuhr et al., 2022), including ones with more robust causal designs (Bertoni et al., 2021), are limited as they focus specifically on the COVID-19 period. This makes it difficult to disentangle mental health impacts of working from home from impacts due to public health restrictions, economic instability, social isolation and infection spread. Most work from home during the pandemic was also 'mandated' or 'forced', which may dilute the pure 'work from home' impact on mental health. The results from these recent studies may hold less relevance with the transition out of public health mandates and lockdown-like conditions (Serrano-Alarcón et al., 2022). The consensus amongst recent studies is that working from home harmed mental health during the pandemic (Niebuhr et al., 2022; Oakman et al., 2022; Schifano et al., 2021; Somasundram et al., 2022). One recent study found, however, evidence of positive mental health impacts amongst men and workers with no co-residing children (Bertoni et al., 2021).

I attempt to overcome some methodological limitations in past studies by using nationally-representative, Australian panel survey data spanning 19 years to estimate the causal relationship between working from home and mental health both before and during the COVID-19 pandemic. I employ two methods of causal inference in my identification strategy; fixed-effects estimation to control for potential heterogeneity bias from time-constant individual level unobservables in the pre-pandemic period (2002-2019), and instrumental variable estimation to control for endogeneity from time-varying unobservables and selection effects. I test the relevance and validity of the chosen instrument, workplace entitlement to home-based work, using first-stage F-tests and support instrument exogeneity by controlling for a large set of covariates and confounders related to workers, their employment and employer characteristics.

Subgroup analyses are performed for the pre-pandemic period to examine the heterogeneity of impacts across worker subgroups. The estimations performed for the pandemic period (2020) draw on the rich nature of dataset by controlling for a range of occurrences specific to the pandemic that may have affected individual mental health, including contracting the coronavirus, having work hours reduced, job termination, taking a pay cut or having to home-school children, in an attempt to isolate the 'pure' impact of working from home.

This study is organised as follows. Section 2 presents the data, variables and sample characteristics (including the outcome variables, covariates, endogenous variable and instrument). Section 3 describes the identification strategy. Section 4 includes the estimation results for the pre-pandemic and pandemic periods and Section 4.3 concludes with a summary of the key findings.

2 Data, variables, and descriptive statistics

I used 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. 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 latest wave to be released, Wave 20, contains information on 7,552 responding households and a total of 18,160 persons, with data collection for this wave taking place during the COVID-19 pandemic, from August 2020 onwards (Summerfield, 2021). All waves before Wave 20 constitute pre-pandemic waves. To conduct the estimations, I used Waves 2-20 as these contained all the variables required to investigate the research question (Melbourne Institute, 2021).

I limited the analysis 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 size varied from 11,420-15,772 workers for the pre-pandemic baseline estimations (Wave 2-19, corresponding to 2002-2019) and 5,708-6,192 workers for the pandemic year estimations (Wave 20, corresponding to 2020).

2.1 Trends in the endogenous variable: time spent working from home

The key covariate of interest ('exposure') in the analysis was time 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, I constructed a dummy variable (WFH_{it}) for each worker (i) in each wave (t) indicating whether this individual spent time working at home (where *1* = any time worked at home and *0* otherwise).

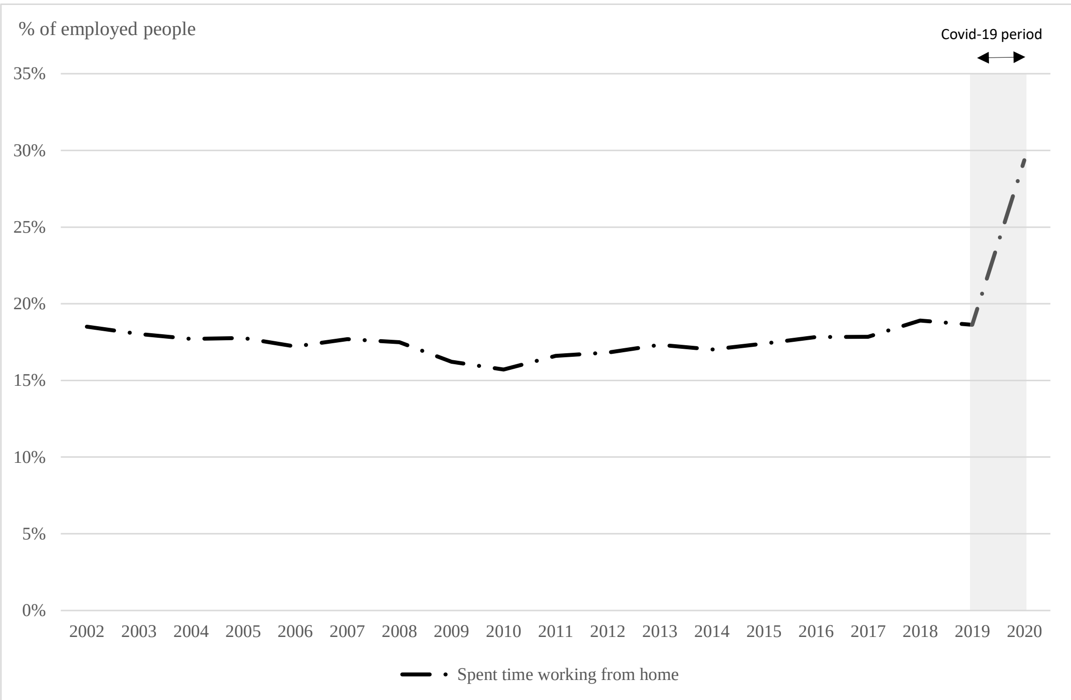
The HILDA survey also asked questions on how many weekly hours an individual usually worked and how many of these were worked at home. Using these survey questions, I also constructed a continuous variable indicating the percentage of total working hours worked from home.

Time spent working at home is likely to be endogenous to mental health outcomes, as certain types of individuals may 'select into' spending more time working at home, due to both observable and unobservable characteristics or life events. People who are diagnosed with psychiatric conditions may utilise greater work flexibility (McDowell & Fossey, 2015) and select into working at home, as may individuals without diagnosed conditions but who experience dips in mental health wellbeing. Furthermore, individuals with certain constant characteristics and personality traits such as shyness and introversion (Jylhä et al., 2009) and an external locus of control (Frenkel et al., 1995; Nowicki et al., 2018) may select into working from home, with these traits potentially associated with worse mental health. Hence, there may be reverse causation between mental health and spending time working at home, with potential selection of individuals with worse mental health into working from home.

Figure *1* shows trends in the proportion of employed people working from home over time in Australia. 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 resulted in a steep increase in this proportion to approximately 29 percent of all workers, due to public health mandates to work from home in Australia and prevent infection spread.

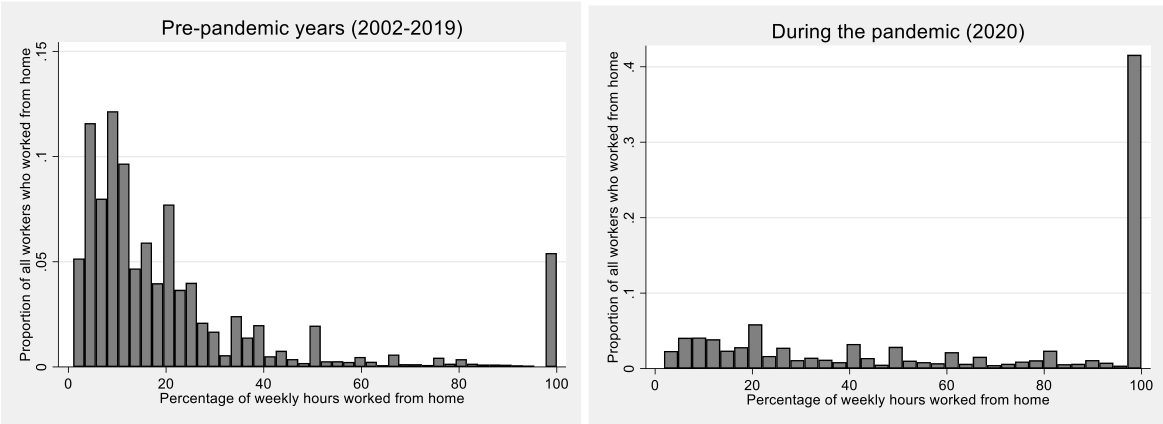
Figure 2 shows the pre-pandemic and pandemic distributions in percentage of weekly hours worked from home. This shows that in pre-pandemic years, the majority of individuals who worked from home worked 0-20% of their weekly hours from home. Within the pre-pandemic distribution, there is still a large 'spike' in the distribution near 100% which identifies a distinct worker group who worked nearly all or all of their weekly hours from home. The pattern for the pandemic year is quite distinct, with over 40% of workers who worked from home indicating they worked nearly all or all of their hours from home, reflecting public health directives to work from home in 2020. Overall, most work from home that occurred in 2020 was at an 'intensive' level (nearly all hours were worked from home).

Figure 1: Employed people working from home over time in Australia (%) (exc. self-employed)



Source: Author's calculations using HILDA data restricted release 20 (Melbourne Institute, 2021)

Figure 2: Percentage of weekly hours worked from home for individuals reporting 'any of their usual working hours worked from home'(a)



(a) Excludes individuals who reported 'varying hours worked from home' or those with missing responses. Source: Author's calculations using HILDA data restricted release 20 (Melbourne Institute, 2021)

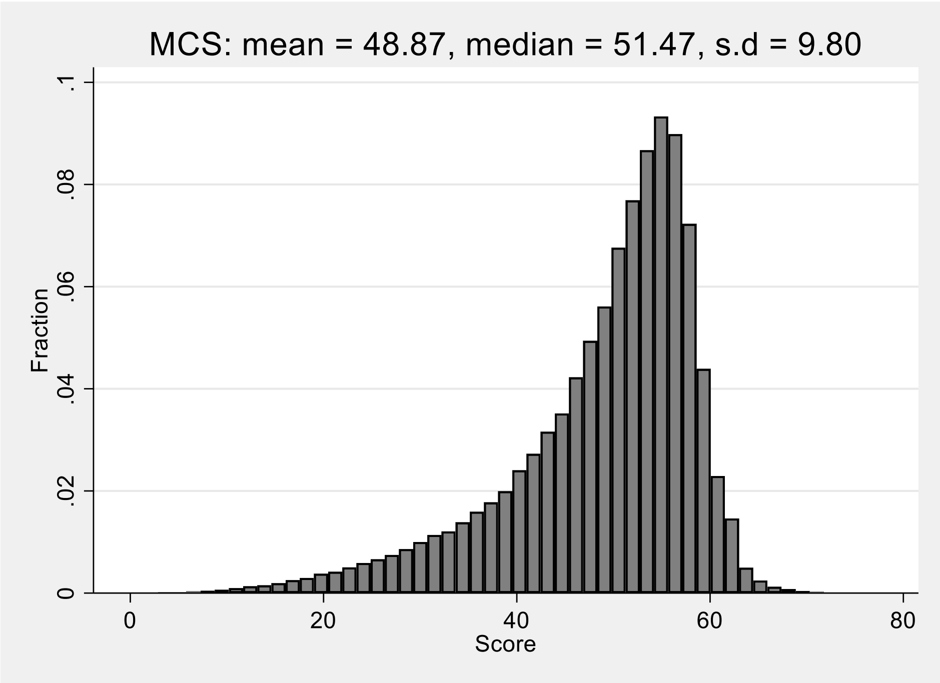
2.2 Mental health outcome variable: distribution and trends

The outcome variable in this analysis (Y_{it}), the Mental Component Summary (MCS), was constructed from answers to questions in the HILDA survey from the Medical Outcomes Study Short Form 36 (SF-36), a widely used self-completion tool used for population and clinical research and screening of psychiatric disorders (Butterworth & Crosier, 2004; Marosszeky & Sansoni, 2005; Ware et al., 2001). The validity of SF-36 data in HILDA has been demonstrated, with all eight health subscales found to be psychometrically robust, internally consistent and reliable (Butterworth & Crosier, 2004).

The MCS is a more expansive measure than the commonly analysed Mental Health Inventory (MHI-5), and is constructed from items across the mental health, vitality, social functioning, general health, bodily pain, physical functioning, and role limits SF-36 subscales[3]. It has better measurement precision and smaller confidence intervals than the MHI-5, and eliminates floor/ceiling effects (Ware et al., 2001). The distribution of the MCS for the employed people sample, reflects this, with less mass around maximum values than typically seen with the MHI-5 (**Figure 3**).

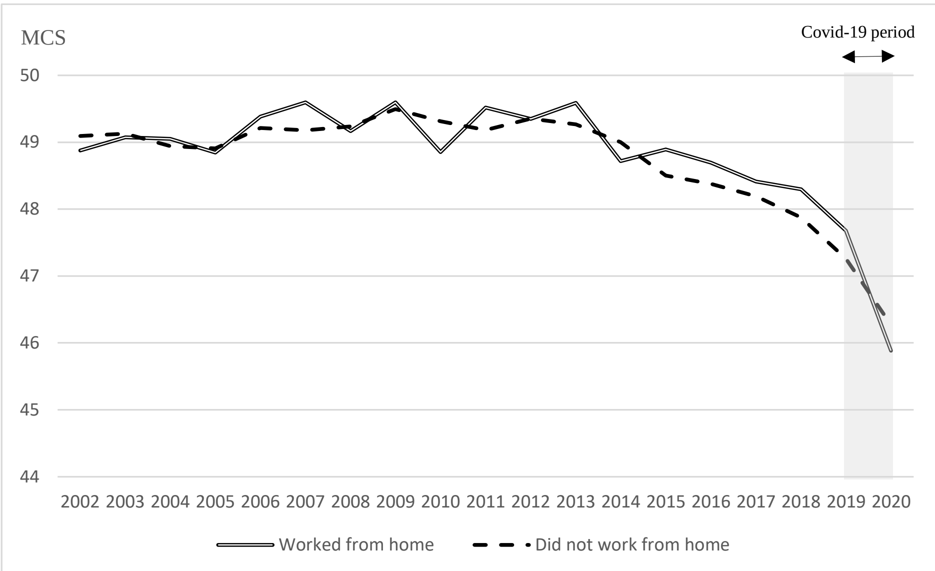
Figure 4 shows the trend in the average MCS for Australian workers over time, including those who worked from home and those who did not. The general trend is declining mental health for all workers over the study period, with very similar average scores between those who worked from home and those who did not. Average mental health deteriorated noticeably for both types of workers during the COVID-19 pandemic. Interestingly, the COVID-19 pandemic led to a steeper deterioration in average self-reported mental health for those who worked from home relative to those who did not.

Figure 3: Distribution of Mental Component Summary for Australian workers (waves 2-20)



Source: Author's calculations using HILDA data restricted release 20 (Melbourne Institute, 2021).

Figure 4: Mean Mental Component Summary (MCS) score for employed people over time



Source: Author's calculations using HILDA data restricted release 20 (Melbourne Institute, 2021).

2.3 Supporting exogeneity of the instrumental variable: workplace entitlement to home-based work

Finding an appropriate instrumental variable (Z_{it}) to disentangle the causal relationship between working from home and mental health is a challenging endeavour. To meet the requirements for an appropriate instrument, Z_{it} must (Angrist & Pischke, 2009):

i. have a clear effect on the endogenous variable, 'any time spent working at home' ($\mathrm{WFH_{it}}$) through the first stage;

ii. affect mental health ($\mathrm{Y_{it}}$) only through the first-stage channel, that is, through its effect on time spent working at home ($\mathrm{WFH_{it}}$); and

iii. be as good as 'randomly assigned' (independent of potential outcomes), conditional on all the included covariates ($\mathrm{X_{it}}$).

The first requirement constitutes instrument relevance, while the second and the third constitute the exclusion restriction (Angrist & Pischke, 2009). Many of the factors strongly associated with spending time working from home (i.e. those meeting requirement (i)), such as life events, the presence of dependent children, caring responsibilities and the onset of health conditions, also likely have a direct impact on an individual's mental health, which would violate (ii).

While 'tele-workability' or the technical feasibility of remote work for an individual (a function of occupation, industry and work nature) is likely to be a good instrument and source of exogeneous variation for mandated remote work in pandemic years (Bertoni et al., 2021), within pre-pandemic years, there is the likelihood of selection into jobs by individuals, based on their tele-workability, which would confound exogeneity of this instrument. Recent tele-workability indices are also unsuitable for a long data panel, as tele-workability is likely to have evolved over time for different work types.

Instead, for the analysis in this study, I used an annual question in HILDA around potential access to home-based work, with the phrasing from Wave 2 onwards being:

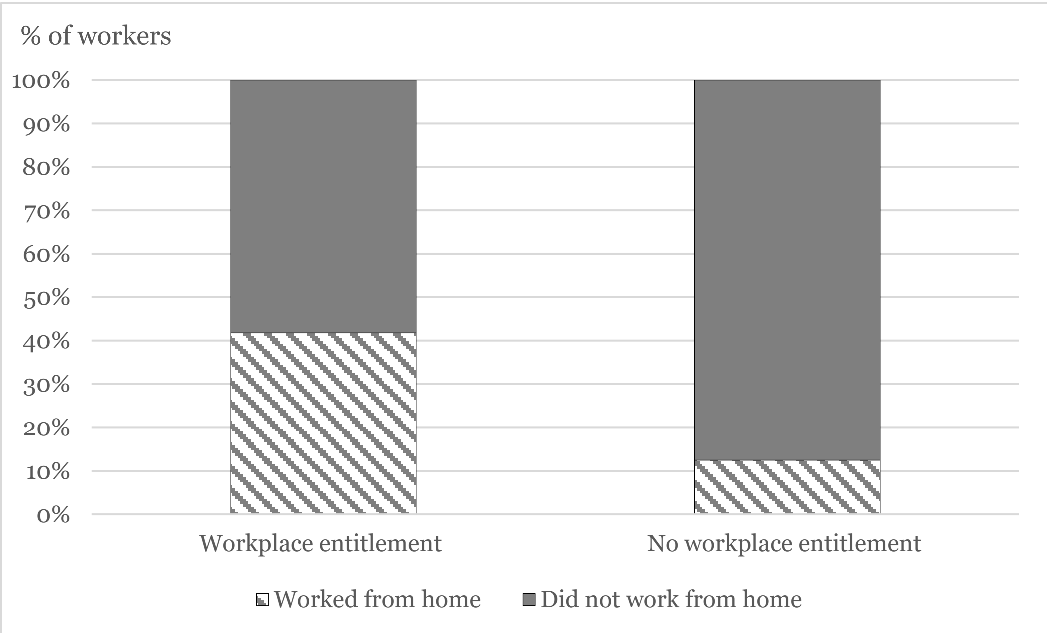
"Following is a list of conditions and entitlements that employers sometimes provide their employees. For each, please indicate whether you, or other employees working at a similar level

to you at your workplace, would be able to use these if needed: - Home-based work" (Melbourne Institute, 2022).

Using this, I constructed a binary instrumental variable (Z_{it}) indicating whether an individual had potential access to home-based work as a workplace entitlement (where *1* = potential access to home-based work as an entitlement and *0* otherwise). This variable represents an organisational attribute rather than a measure of actual worker behaviour (Milner et al., 2018).

Figure 5 shows this variable strongly meets the relevance requirement (i), with workplace entitlement having a clear positive correlation with whether an individual actually spent time working from home. Of those workers reporting an entitlement to home-based work, just over 40 per cent actually spent time working from home, compared to 12 percent of those reporting no workplace entitlements.

Figure 5: Percentage of workers working from home by workplace entitlement (waves 2-20)



Source: Author's calculations using HILDA data restricted release 20 (Melbourne Institute, 2021)

I posit that this variable is likely to also meet condition (ii) for a valid instrument, as it is unlikely that an entitlement to home-based work would materially affect a worker's mental health independent of whether the worker actually used the entitlement. One plausible, but empirically weak separate channel could be through the effect of this entitlement on job satisfaction (Wooden

& Warren, 2004), and then through job satisfaction to mental health (Faragher et al., 2013; Pearson, 1998). To account for this weak possibility of an alternative channel, I controlled for past-year job satisfaction as a dummy variable in all estimations.

The main threat to identification is the violation of condition (iii) through instrument endogeneity, that is, individuals selecting into 'workplace entitlements to home-based work' either through negotiation, changing occupations or changing employers (i.e. changing jobs). Plausibly, it is easier for workers to 'select into' spending time working from home rather than changing employers, occupations, and employment conditions.

Nonetheless, workplace entitlement to home-based work is itself related to the feasibility of remote work for an individual, which is shaped by occupation, industry, location and work type (United States Bureau of Labor Statistics, 2020). Therefore, the distribution of workplace entitlements cannot be taken as 'randomly assigned' (Angrist & Pischke, 2009). Hence, it is important to support the exogeneity of workplace entitlements as an instrument (Baktash et al., 2022) by conditioning on all covariates related to both the feasibility of home-based work and to the potential selection by individuals into workplace entitlements (e.g. worker mobility) (Angrist & Pischke, 2009).

To support instrument exogeneity, I controlled for an expansive range of worker, employment and employer-related covariates and confounders likely to be related to the distribution of workplace entitlements across workers (see **Table *1***), including occupation type (seven dummies), industry (fifteen dummies) and region (eight dummies related to State or Territory). I also controlled for characteristics of the employer related to the likelihood of offering workplace entitlements to home-based work, including employer size, whether the employer was in multiple locations (e.g. multi-state or multinational firm) and whether the employer was a for-profit, not-for-profit or government organisation. Worker and work type characteristics included whether an individual worked full-time, had supervisory responsibilities at work, was a member of a trade union, was employed through a labour-hire firm, and their contract type.

Lastly, I controlled for several variables relating to the potential selection of workers into entitlements, including self-reported changes in jobs or occupation type in the past year. The

Australian Government introduced a right to request 'flexible work arrangements' in 2009 to workers with caring responsibilities of a child under school age or a child with a disability, under the *Fair Work Act 2009*. Eligibility extended to workers with at least 12 months' continuous service, or long-term casuals (Commonwealth of Australia, 2009), with approval depending on employer discretion and 'reasonable business grounds'. In 2013, the Government amended the *Fair Work Act 2009* to extend this right to more worker groups, including carers, workers with disabilities, workers experiencing domestic violence and workers aged 55 years or older (Commonwealth of Australia, 2013).

These policy changes affected subsets of individuals observed in the estimation sample within particular timeframes (from 2009 and 2013 onwards), after which they may have induced potential selection into workplace entitlements to home-based work (the instrument) through negotiations by workers with certain characteristics[5]. To account for potential selection into entitlements based on these characteristics, I controlled for disability (through a long-term health condition dummy), number of dependent children, birth of a child in the past year, turning 55 years or older, becoming an informal carer, and being a victim of violence through the inclusion of dummy variables.

2.4 Other covariates

As noted in the previous section, the main motivation behind covariate selection was to strongly support the exogeneity of the chosen instrument, workplace entitlement to home-based work. However, other covariates were also included to account for individual-level characteristics and life events related to mental health, selected through a review of literature on the determinants of health outcomes (Bilgrami et al., 2020; Contoyannis et al., 2004; Hauck & Rice, 2004). HILDA is ideally suited to conducting analysis on mental health as it includes a rich set of self-reported information on demographics, income, occupation, life events and health conditions over time, as well as detailed questions related to an individual's experiences during the pandemic in 2020.

The covariates selected (see **Table *1***) included socio-demographic characteristics such as age, gender, marital status, and number of dependent children (noting that only time-varying covariates were retained in the fixed-effects estimations). Specific self-reported life events in the past year causing temporary fluctuations in mental health (Roy & Schurer, 2013) were also controlled for. Weekly hours worked and years worked in a person's current job were included, to capture the impact of job-related stressors (Fletcher et al., 2011; Milner et al., 2018).

The presence of a long-term health condition was included, which captures disabilities and disabling chronic conditions, including any mental illnesses requiring help or supervision.

The logarithm of equivalised, past-year household income was also included to allow for concavity in the health-income relationship (Hauck and Rice, 2004). Similar to Bilgrami et al. (2020) and Hauck and Rice (2004), I assumed income and mental health were not simultaneously determined because the income measure used was past-year household income, while the mental health outcomes captured recent changes in health (i.e. 'over the past four weeks').

In the estimations conducted for the pandemic year (2020), an additional set of event dummies were included to control for unique occurrences specific to the pandemic that may have affected mental health, including contracting the coronavirus, having work hours reduced, job termination, being temporarily stood down, taking a pay cut or home-schooling children. Finally, year dummies were included in the pre-pandemic estimations to account for temporal fluctuations in population mental health over the relatively long estimation time period (2002-2019).

Table 1: Covariate averages for employed people by working from home status

	(A) Pre-pandemic (pooled observations waves 2-19)				*(B) During the pandemic (wave 20 observations)*			
	Did not work from home		*Worked from home*		*Did not work from home*		*Worked from home*	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*	*N*	*Mean*
Age (years)	121,938	36.902	25,843	42.554	6,358	37.959	2,643	41.964
Female (0/1)	121,938	0.503	25,843	0.519	6,358	0.509	2,643	0.552
Dependent children (number)	121,938	0.641	25,843	0.927	6,358	0.673	2,643	0.858
Married/de-facto (0/1)	121,928	0.606	25,842	0.777	6,357	0.623	2,643	0.773
Log of equiv. household disposable income ($)[(a)]	121,776	10.953	25,792	11.160	6,355	11.004	2,641	11.249
Highest educational attainment								
High school or less	121,938	0.434	25,843	0.189	6,358	0.381	2,643	0.149
Certificate/diploma	121,938	0.330	25,843	0.259	6,358	0.368	2,643	0.243
Tertiary degree	121,938	0.236	25,843	0.551	6,358	0.251	2,643	0.608
Long-term health cond. (0/1)	121,910	0.156	25,843	0.164	6,357	0.181	2,643	0.154
Lives in metropolitan area (0/1)	121,929	0.677	25,842	0.738	6,356	0.636	2,643	0.822
In full-time work (0/1)	121,938	0.645	25,843	0.781	6,358	0.604	2,643	0.769
Contract type (0/1)								
Permanent	121,603	0.654	25,324	0.767	6,345	0.685	2,631	0.813
Casual	121,603	0.255	25,324	0.092	6,345	0.251	2,631	0.067
Contractor/other	121,938	0.091	25,843	0.138	6,358	0.064	2,643	0.119
Employer type (0/1)								
For-profit	121,938	0.694	25,843	0.541	6,358	0.685	2,643	0.544
Government organisation	121,938	0.184	25,843	0.298	6,358	0.198	2,643	0.296
Not-for-profit/other	121,938	0.122	25,843	0.161	6,358	0.117	2,643	0.160
Multiple location employer (0/1)	121,938	0.678	25,843	0.745	6,358	0.688	2,643	0.770
Organisation size (0/1)								
20 people or less	121,938	0.369	25,843	0.317	6,358	0.351	2,643	0.283
20-100 people	121,938	0.307	25,843	0.329	6,358	0.325	2,643	0.283
100+ people	121,938	0.322	25,843	0.352	6,358	0.318	2,643	0.431
Member of trade union (0/1)	121,938	0.243	25,843	0.303	6,358	0.236	2,643	0.228
Employed through labour-hire or temp. agency (0/1)	121,938	0.029	25,843	0.011	6,358	0.020	2,643	0.012
Supervisor responsibilities (0/1)	121,938	0.441	25,843	0.579	6,358	0.412	2,643	0.484
Hours worked per week (hours)	118,294	34.885	25,189	41.343	6,211	33.540	2,621	38.835

	(A) Pre-pandemic (pooled observations waves 2-19)				(B) During the pandemic (wave 20 observations)			
	Did not work from home		Worked from home		Did not work from home		Worked from home	
	N	Mean	N	Mean	N	Mean	N	Mean
Tenure in current job (years)	92,205	7.383	22,542	9.890	5,152	7.720	2,322	8.612
Changed job in past year (0/1)	121,938	0.188	25,843	0.126	6,358	0.162	2,643	0.134
Changed occupation in past year (0/1)	121,938	0.190	25,843	0.141	6,358	0.161	2,643	0.148
Past-year job satisfaction (satisfied with job)[(b)] (0/1)	121,879	0.951	25,833	0.965	6,354	0.972	2,642	0.973
Occupation type (0/1):								
Managers	121,873	0.083	25,831	0.236	6,358	0.082	2,642	0.235
Professionals	121,873	0.185	25,831	0.490	6,358	0.179	2,642	0.465
Technicians and trades	121,873	0.139	25,831	0.048	6,358	0.138	2,642	0.045
Community & personal services	121,873	0.137	25,831	0.048	6,358	0.161	2,642	0.048
Clerical and administrative	121,873	0.110	25,831	0.045	6,358	0.112	2,642	0.030
Sales	121,873	0.161	25,831	0.104	6,358	0.128	2,642	0.164
Machine operators/labourers	121,873	0.185	25,831	0.029	6,358	0.200	2,642	0.012
Industry type (0/1)								
Agriculture, forestry and fishing	121,938	0.020	25,843	0.025	6,358	0.021	2,643	0.009
Mining	121,938	0.019	25,843	0.011	6,358	0.023	2,643	0.013
Manufacturing	121,938	0.096	25,843	0.063	6,358	0.088	2,643	0.059
Electricity/gas/water	121,938	0.008	25,843	0.006	6,358	0.005	2,643	0.016
Construction	121,938	0.066	25,843	0.035	6,358	0.071	2,643	0.040
Wholesale trade	121,938	0.026	25,843	0.040	6,358	0.024	2,643	0.028
Retail trade	121,938	0.135	25,843	0.040	6,358	0.141	2,643	0.033
Restaurants and hotels	121,938	0.081	25,843	0.018	6,358	0.080	2,643	0.012
Finance and insurance	121,938	0.032	25,843	0.049	6,358	0.016	2,643	0.083
Transport and storage	121,938	0.044	25,843	0.023	6,358	0.046	2,643	0.020
Communication and services	121,938	0.015	25,843	0.019	6,358	0.010	2,643	0.017
Cultural and recreational activities	121,938	0.034	25,843	0.039	6,358	0.026	2,643	0.042
Other services	121,938	0.103	25,843	0.156	6,358	0.085	2,643	0.185
Education/Govt. admin/other	121,938	0.163	25,843	0.389	6,358	0.149	2,643	0.328
Health	121,938	0.159	25,843	0.086	6,358	0.215	2,643	0.114
Life events in past year (0/1)								
Gave birth	108,492	0.033	23,448	0.043	5,775	0.038	2,475	0.036
Death of relative	108,559	0.114	23,467	0.108	5,778	0.117	2,477	0.106
Separated from partner	108,511	0.043	23,458	0.031	5,773	0.044	2,477	0.031
Death of spouse or child	108,484	0.004	23,463	0.004	5,774	0.003	2,477	0.002

	(A) Pre-pandemic (pooled observations waves 2-19)				*(B) During the pandemic (wave 20 observations)*			
	Did not work from home		***Worked from home***		***Did not work from home***		***Worked from home***	
	N	***Mean***	***N***	***Mean***	***N***	***Mean***	***N***	***Mean***
Death of friend	108,532	0.082	23,463	0.079	5,778	0.089	2,477	0.075
Fired from job	108,497	0.033	23,464	0.019	5,775	0.040	2,477	0.024
Turned 55 years+	121,938	0.128	25,843	0.177	6,358	0.171	2,643	0.187
Became an informal carer	121,938	0.055	25,843	0.081	6,358	0.060	2,643	0.073
Victim of violence	121,938	0.013	25,843	0.008	6,358	0.014	2,643	0.008
Occurrences related to the COVID-19 pandemic (0/1):								
Tested positive for coronavirus	-		-		6,358	0.006	2,643	0.008
Worked reduced hours	-		-		6,358	0.236	2,643	0.157
Job terminated	-		-		6,358	0.024	2,643	0.010
Temporarily stood down	-		-		6,358	0.093	2,643	0.039
Took pay cut	-		-		6,358	0.054	2,643	0.077
Home-schooled children	-		-		6,358	0.283	2,643	0.303

Source: Author's calculations using HILDA data restricted release 20 (Melbourne Institute, 2021).

(a) Converted to $ AUD in 2020—adjusted by the wage price index from the Australian Bureau of Statistics (ABS) (2022). (b) Constructed as a binary variable with '1' indicating a score of 5 or greater (on a scale of 1-10) on overall self-rated job satisfaction in the wave prior, and 0 otherwise.

3 Identification strategy

The aim of the analysis was to estimate the causal impact of time spent working from home on mental health in both pre-pandemic years and during the pandemic. In an ideal world, this would involve estimating differences in mental health outcomes between perfectly matched individuals who differed only on whether they worked from home and were subject to the same life events and circumstances. Due to the implausibility of such a situation, and due to potential endogeneity between mental health and working from home, as individuals with certain characteristics and in certain circumstances are likely to 'select into' working from home, I employed an IV identification strategy.

I combined IV with another causal inference method, fixed effects (FE) estimation, for the pre-pandemic period (2002-2019), by exploiting the panel nature of HILDA to estimate changes *within* individuals (with each individual acting as their own counterfactual when they switch into and out of working from home). FE removes the impact of time-constant individual-level unobservable characteristics which may be correlated with covariates or the outcome measure, and bias estimated effects through potential heterogeneity bias (Reichert & Tauchmann, 2017). Some potentially time-invariant individual-level factors associated with mental health outcomes may include introversion (Jylhä et al., 2009) and locus of control (Frenkel et al., 1995; Nowicki et al., 2018).

The reduced-form equation for the analysis of working from home on mental health is:

$$Y_{it} = \beta_0 + \beta_1 WFH_{it} + \beta_n X_{it} + \eta_i + u_{it} \text{ .... (1)}$$

where Y_{it} is the continuous MCS score for individual i at time t, WFH_{it} is a binary variable indicating whether individual i spent any time working from home at time t, X_{it} are a set of n covariates for individual i at time t, η_i is the time-constant individual-specific component of the error term and u_{it} is the idiosyncratic error term (time-varying unobservables). FE estimation removes the time-constant individual-specific component of the error (η_i).

Estimating (1) through FE may still produce a biased estimate of β_1 if WFH_{it} is correlated with the idiosyncratic error (u_{it}), due to the potential selection of individuals into working from home due to time-varying unobservables. This may occur despite controlling for an extensive set of observable, time-varying confounders and life events, X_{it}. There may also be reverse causation from mental health to working from home, with individuals experiencing temporarily worse mental health potentially 'selecting into' working from home.

Using an IV (Z_{it}), can assist in identifying the causal effect of working from home (WFH_{it}) on mental health (Y_{it}), by isolating the part of the variation in WFH_{it} that is uncorrelated with u_{it}. For this analysis, I used workplace entitlement to home-based work for individual i at time t, a dummy variable, as the IV (Z_{it}). In the first stage, the following equation linking WFH_{it} and Z_{it} was estimated via FE for pre-pandemic years:

$$WFH_{it} = \pi_0 + \pi_1 Z_{it} + \pi_n X_{it} + \partial_i + v_{it} \text{ ………. (2)}$$

The second stage FE-IV estimation uses only the part of the variation in WFH_{it} that is uncorrelated with u_{it} ($\widehat{WFH}_{it} = \pi_0 + \pi_1 Z_{it} + \pi_n X_{it}$) in (2) to identify the causal impact of working from home on mental health outcomes. If the assumptions for instrument relevance and validity described in Section 2.3 are met, conditional on the included covariates, then IV estimation would produce an unbiased estimate of β_1, that is, the causal effect of working from home on mental health.

To separately analyse the pandemic period in this study (Wave 20, 2020), I employed ordinary least squares (OLS) and OLS-IV estimation to estimate mental health impacts of working from home for the Wave 20 cross-section.

Additional subgroup analyses were conducted for the pre-pandemic period to examine heterogeneity in the mental health impacts of working from home. These were done by performing IV estimations separately for different worker groups, including males, females, people with and without dependent children and people in single and multi-person households. Estimations were also conducted for the continuous indicator, percentage of hours worked from home (as in **Figure 2**), for both pre-pandemic and pandemic years.

4 Estimation results

4.1 Mental health impacts in pre-pandemic years

Table 2 presents the estimation results for the pre-pandemic period after controlling for the expansive list of selected covariates. Under pooled OLS regression (column 1), time spent working at home was associated with significantly worse mental health. These estimates do not control for potential heterogeneity bias from time-constant individual-level unobservable traits and do not account for potential selection of individuals into working from home (endogeneity from reverse causality). The negative sign on the estimated OLS coefficient aligns with the hypothesis that individuals with worse mental health may select into working from home.

FE regression estimates (column 3), remove potential heterogeneity bias by estimating within-individual changes, and show insignificant impacts of working from home on mental health. However, these estimates may still suffer from endogeneity if working from home is correlated with the idiosyncratic error, due to time-varying unobservables not controlled for.

Columns 2 and 4 present the IV estimates for the pooled OLS and FE regressions, using workplace entitlement to home-based work as an IV. In terms of instrument strength, the large first-stage F-statistics (Baum et al., 2007) in **Table 2**, strongly indicate that weak instrumentation is not an issue. Endogeneity tests for the IV models[4] in columns 2 and 4 suggest that the null hypothesis of exogeneity of time spent working at home can be strongly rejected, and that it is appropriate to run IV regressions.

The IV regression estimates (columns 2 and 4) show that working from home significantly boosted mental health in the pre-pandemic period. The FE-IV regression (column 4) is the preferred specification, as it controls for both potential heterogeneity bias and for endogeneity. Under this specification, working from home significantly increased an employed individual's MCS by 1.92 points (0.2 standard deviations), with results statistically significant at the 5% level.

Table 2: Estimated effect of working from home and selected covariates on mental health (MCS) – Pre-COVID-19 pandemic[(a)] (Waves 2-19)

	(1) OLS			(2) OLS IV			(3) FE			(4) FE-IV		
	Coeff.	**S.E**	**P**	**Coeff.**	**S.E**	**P**	**Coeff.**	**S.E**	**p**	**Coeff.**	**S.E**	**p**
Any hours worked from home	-0.503***	0.136	0.000	1.360*	0.755	0.072	-0.051	0.094	0.583	1.921**	0.831	0.021
Age (years)	-0.214***	0.033	0.000	-0.201***	0.035	0.000	-0.281	0.039	0.000	-0.319***	0.043	0.000
Age-squared	0.004***	0.000	0.000	0.003***	0.000	0.000	0.003	0.000	0.000	0.004***	0.000	0.000
No. of dependent children	-0.030	0.064	0.634	-0.098	0.069	0.151	-0.319***	0.058	0.000	-0.371***	0.062	0.000
Married/De-facto	1.209***	0.154	0.000	1.219***	0.160	0.000	0.558***	0.143	0.000	0.619***	0.158	0.000
Log of equiv. household disposable income ($ AUD)[(b)]	0.958***	0.121	0.000	0.957***	0.128	0.000	0.140	0.094	0.135	0.136	0.101	0.177
Has long-term health condition	-3.584***	0.159	0.000	-3.577***	0.168	0.000	-0.989***	0.105	0.000	-0.947***	0.112	0.000
Death of relative	-0.799***	0.110	0.000	-0.804***	0.117	0.000	-0.775***	0.085	0.000	-0.753***	0.092	0.000
Separated from partner	-3.971***	0.251	0.000	-4.031***	0.274	0.000	-3.188***	0.212	0.000	-3.236***	0.234	0.000
Death of spouse or child	-4.509***	0.685	0.000	-4.985***	0.767	0.000	-4.118***	0.586	0.000	-4.532***	0.632	0.000
Victim of violence	-4.361***	0.459	0.000	-4.207***	0.500	0.000	-1.842***	0.402	0.000	-1.936***	0.434	0.000
N (observations)	*88,917 (15,772 individuals)*			*75,793 (14,776 individuals)*			*88,917 (15,772 individuals)*			*72,437 (11,420 individuals)*		
R^2	0.084			0.079			0.021			0.015		
First-stage F	-			691.517			-			444.424		

OLS-IV and FE-IV are ordinary least squares (OLS) and fixed effects (FE) instrumental variables regression results using workplace entitlement to home-based work as an instrument. Standard errors clustered at the individual level. Table note **(a)** Included in each specification but not shown is a full set of year dummies and the full list of covariates presented in Table 1. Full modelling results available from author. **(b)** Converted to Australian Dollars ($ AUD) in 2020—adjusted by the wage price index from the Australian Bureau of Statistics (ABS) (2022). *p<0.1*, p<0.05**, p<0.01****

4.1.1 Subgroup analyses for different worker groups in pre-pandemic years

Table 3 shows FE-IV estimated effects of working from home on mental health for different worker groups in the pre-pandemic period. Large and significant improvements in mental health were estimated for particular groups, including males, those with dependent children, those living in multi-person households and workers who had been with their employer for greater than one year. Conversely, insignificant impacts were estimated for their comparator groups (females, those without dependent children, those in single person households, those working less than a year at their employer).

These subgroup results may be explained through the Grossman model (Grossman, 1972). Significant benefits for those with dependent children may relate to the better use of additional free time on mental health production through increased recreation and leisure time spent with children. Insignificant mental health benefits for those living in single-person households may relate to displacement of workplace socialising by increased isolation at home, which may harm mental health.

The heterogeneity of mental health impacts by time spent at employer may relate to the 'investment' side aspect to health in the Grossman model. Namely, workers with less than one year of experience at an employer are likely to be those most in need of regular contact with colleagues, guidance, and training. Working from home may jeopardise the ability to effectively participate in their employment ('income production') or hinder career progression for such workers, which may explain the negative sign of the insignificant coefficients estimated for this group. The most striking result is the insignificant effect estimated for females. Further research is needed to identify whether this result may relate to an unequal sharing of caring responsibilities and burden from dual worker/caregiver roles for women (Dunatchik et al., 2021) or whether working from home may harm career prospects and job progression due to reduced visibility for women who work from home[6].

Table 3: FE-IV Estimated effect of working from home on mental health (MCS) for worker subgroups – Pre-COVID-19 pandemic[(a)] (Waves 2-19)

	Coeff	S.E	P
Females	1.084	1.116	0.331
N (observations)	*37,147 (5,903 individuals)*		
First-stage F	269.689		
Males	3.187**	1.245	0.010
N (observations)	*35,287 (5,516 individuals)*		
First-stage F	182.430		
No dependent children	0.325	1.368	0.812
N (observations)	*39,909 (8,044 individuals)*		
First-stage F	200.565		
Has dependent children	3.337***	1.285	0.009
N (observations)	*30,921 (5,325 individuals)*		
First-stage F	164.896		
Lives in single-person household	1.099	3.302	0.739
N (observations)	*8,656 (1,900 individuals)*		
First-stage F	38.165		
Lives in multi-person household	1.992**	0.864	0.021
N (observations)	*62,578 (10,313 individuals)*		
First-stage F	388.723		
Years worked ≤ 1	-2.009	3.413	0.556
N (observations)	*3,276 (1,447 individuals)*		
First-stage F	32.129		
Years worked > 1	2.406***	0.927	0.009
N (observations)	*64.880 (10,496 individuals)*		
First-stage F	347.961		

Standard errors clustered at the individual level. Table note (a) Included in each specification but not shown is a full set of year dummies**.** *p<0.1*, p<0.05**, p<0.01****

4.2 Mental health impacts during the pandemic

Due to the unique set of circumstances created by the pandemic and the largely 'forced' uptake of working from home from the imposition of public health mandates, the mental health impacts of working from home may have differed during the pandemic.

Table 4 shows the results of the OLS (column 1) and OLS-IV (column 2) estimations for the pandemic period, after controlling for all confounders including occurrences specific to the pandemic in Australia. These included dummies for being in Victoria, which had both the highest rate of infection spread and the harshest lockdown of all regions (O'Donnell et al., 2022), home-schooling children and experiencing adverse job-related impacts. Both the OLS and OLS-IV estimates indicate a deterioration in mental health due to largely mandated working from home during the pandemic (a -0.17 standard deviation decline in the OLS-IV estimate in column 2).

Table 4: Estimated effect of working from home and selected covariates on mental health (MCS) during the COVID-19 pandemic (Wave 20)

	(1) OLS			(2) OLS-IV		
	Coeff.	**S.E**	**P**	**Coeff.**	**S.E**	**P**
Any time spent working from home	-0.862**	0.333	0.010	-1.706*	0.988	0.084
Tested positive for coronavirus	2.597*	1.572	0.099	2.476	1.619	0.126
Worked reduced hours	-0.501	0.356	0.160	-0.396	0.365	0.278
Job terminated	0.768	2.171	0.723	0.664	2.479	0.789
Temporarily stood down	-0.177	0.585	0.762	-0.339	0.609	0.578
Took pay cut	-0.284	0.574	0.621	-0.327	0.607	0.590
Home-schooled children	0.317	0.381	0.405	0.415	0.394	0.292
Victoria	-1.309***	0.351	0.000	-1.393***	0.369	0.000
N (individuals)	*6,192*			*5,708*		
R^2	0.134			0.139		
First-stage F	-			597.892		

OLS-IV is ordinary least squares regression results using workplace entitlement to home-based work as an instrument. Table note: Included in each specification is the full list of covariates presented in Table 1. Full modelling results available from author. Standard errors clustered at the individual level. *p<0.1*, p<0.05**, p<0.01****

4.3 Mental health impacts by intensity of home-based work

Analysis was conducted for the intensity of home-based work on mental health in both pre-pandemic years and during the pandemic, using a continuous variable indicating percentage of weekly hours (%) a worker worked from home.

The IV results in **Table 5** indicate that a 10% increase in weekly hours worked from home significantly increased MCS scores by 1.05 points (0.11 standard deviations), on average, in the pre-pandemic period. Conversely, a 10% increase in weekly hours worked from home significantly decreased MCS scores by 0.6 points (0.06 standard deviations), on average, in the pandemic year (2020). These results should be interpreted through the distributions of weekly hours worked in pre-pandemic and pandemic periods (**Figure 2**). In the pre-pandemic period, most workers worked 0-20% of weekly hours from home, while during the pandemic, workers were working high-intensities of (nearly all) weekly hours from home, due to public health mandates.

Overall, these results are suggestive of potential mental health benefits when increasing the intensity of home-based work from a low base and may suggest that mental health benefits drop off at higher intensities. It should be noted that these estimates apply to a select sample, that is, the subset of workers reporting their working hours and without 'varying work hours', hence they may not be generalisable.

Table 5: *IV e*stimated effect of working from home on mental health (MCS) *by intensity*

	Pre-pandemic (waves 2-19)			*Pandemic (wave 20)*		
(A)	**Coeff**	**S.E**	**P**	**Coeff**	**S.E**	**P**
1 per cent increase in weekly hours worked from home	0.105*	0.050	0.053	-0.060**	0.025	0.018
N (observations)	*13,913 (2,939 individuals)*			*1873*		
First-stage F	56.391					

Standard errors clustered at the individual level. Table note: Excludes those with varying working hours. *p<0.1*, p<0.05**, p<0.01****

5 Discussion

This study aimed to estimate the relationship between working from home and mental health and is the first study to compare estimates for the pre-pandemic and pandemic periods, with results generalisable to the broader population due to the use of national data covering all industries and occupations.

Using FE-IV estimation, mental health benefits due to working from home were estimated in the in the pre-pandemic period (0.2 standard deviation gain in the MCS, on average), and applied to particular worker groups including males, workers in multi-person households, workers with longer tenure, and workers with dependent children.

The finding of mental health benefits from working from home aligns with several past studies conducted in the pre-pandemic period (Anderson et al., 2015; Butler et al., 2009; Hokke et al., 2021; Shepherd-Banigan et al., 2016). This finding hinges on the exogeneity of the chosen instrument, workplace entitlement to home-based work, which was supported through the inclusion of an extensive list of covariates related to workers, their work and their employers, and potential worker selection into entitlements due to events or changes in circumstances.

Nonetheless, even without the use of IV estimation, FE estimation suggests that working from home in pre-pandemic years did not harm worker mental health, which may relate to both its discretionary nature and its low intensity during this period, with most workers who worked from home working 0-20% of the time from home. This study illustrates the importance of accounting for reverse causality and selection bias in estimating the relationship between working from home and mental health, as workers in worse mental health may 'select into' working from home, which may confound estimations based on single cross-sections of data.

Conversely, both IV and non-IV estimations suggest that working from home during the pandemic deteriorated worker mental health (by -0.17 standard deviations in the IV estimation). Worse mental health during the pandemic may relate to the largely 'forced' nature of working from home during this time as well as its high intensity, with most workers working nearly all their time from home due to public health mandates. This finding of negative mental heaelth effects aligns with recent studies examining the impact of working from home during the pandemic (Niebuhr et al., 2022; Oakman et al., 2022; Schifano et al., 2021; Somasundram et al., 2022).

Overall, this study provides suggestive evidence that enabling work from home and other flexible work practices may hold promise in terms of boosting worker mental wellbeing in the future. However, a 'one size fits all' or prescriptive approach to policy design may be inappropriate, as the pandemic results show the potentially negative impacts of forced and high-intensity home-based work. Furthermore, some worker groups may be more likely to leverage mental health benefits than others, which may be explained via differing abilities to utilise extra time gained through working from home on health-producing activities. These groups may have a greater preference for working from home than others, which would need to be considered in policy design. The design of remote work policies should be flexible enough to accommodate individual needs and choices and enable additional support for workers such as recent hires who may need more in-office contact and support from experienced colleagues to deliver work.

More research is needed to examine whether there is an average 'optimal' intensity of home-based work, as this will assist in designing future hybrid work policies. The insignificant FE-IV estimated mental health impacts for women working from home in the pre-pandemic period also warrants further research attention, in particular to explore whether this may relate to burden from dual caregiver/worker roles (Dunatchik et al., 2021), or whether working from home may reduce workplace visibility and hinder career progression for women.

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’ and ‘employer/self-employed’.

[3] The scores (0–100) for all items were standardised to z-scores using Australian population means and standard deviations and then aggregated and weighted using factor score coefficients from the Australian Bureau of Statistics (ABS) (1997) with the final aggregated score adjusted to have a mean of 50 and standard deviation of 10 (Ware et al., 2001).

[4] Endogeneity test statistics (Baum et al., 2007) were 6.715 ($p<0.01$) for the OLS-IV model and 5.810 ($p<0.05$) for the FE-IV model. These indicate rejection of the null hypothesis that time spent working at home can be treated as exogenous.

[5] Although negotiations under the *Fair Work Act 2009* do not necessarily translate to guaranteed access to flexible work entitlements, as this depends on the employer approving requests on ‘reasonable business grounds’ (Commonwealth of Australia, 2013).

[6] 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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