MELBOURNE INSTITUTE
Applied Economic & Social Research

Working Paper Series

The effects of commuting and working from home arrangements on mental health

Ferdi Botha
Jan Kabátek
Jordy Meekes
Roger Wilkins

Working Paper No. 15/23
November 2023

THE UNIVERSITY OF MELBOURNE

MELBOURNE INSTITUTE
APPLIED ECONOMIC & SOCIAL RESEARCH

60 YEARS IMPACT

The effects of commuting and working from home arrangements on mental health

Ferdi Botha
Melbourne Institute: Applied Economic & Social Research,
The University of Melbourne

Jan Kabátek
Melbourne Institute: Applied Economic & Social Research,
The University of Melbourne

Jordy Meekes
Department of Economics, Leiden University, Netherlands

Roger Wilkins
Melbourne Institute: Applied Economic & Social Research,
The University of Melbourne

Melbourne Institute Working Paper No. 15/23
November 2023

* This paper uses unit record data from Household, Income and Labour Dynamics in Australia Survey [HILDA] conducted by the Australian Government Department of Social Services (DSS). The findings and views reported in this paper, however, are those of the authors and should not be attributed to the Australian Government, DSS, or any of DSS' contractors or partners. DOI: 10.26193/0LPD4U. This research was supported by the Australian Government through the Australian Research Council's Centre of Excellence for Children and Families over the Life Course (Project ID CE200100025).
Corresponding author: ferdi.botha@unimelb.edu.au.

Melbourne Institute: Applied Economic & Social Research
The University of Melbourne
Victoria 3010 Australia
T +61 3 8344 2100
F +61 3 8344 2111
E melb-inst@unimelb.edu.au
W melbourneinstitute.unimelb.edu.au

Abstract

In this study, we quantify the causal effects of commuting time and working from home (WFH) arrangements on the mental health of Australian men and women. Leveraging rich panel-data models, we first show that adverse effects of commuting time manifest only among men. These are concentrated among individuals with pre-existing mental health issues, and they are modest in magnitude. Second, we show that WFH arrangements have large positive effects on women's mental health, provided that the WFH component is large enough. The effects are once again concentrated among individuals with pre-existing mental health issues. This effect specificity is novel and extends beyond Australia: we show that it also underlies the adverse effects of commuting time on the mental health of British women. Our findings highlight the importance of targeted interventions and support for individuals who are dealing with mental health problems.

JEL classification: D1, I1, R41

Keywords: mental health, commuting, working from home, unconditional quantile regression

1. INTRODUCTION

One of the defining characteristics of modern urban environments is the steady growth of commuting times between homes and places of employment (Giménez-Nadal et al., 2022; Burd et al., 2021). The causes of this development are numerous, and few (if any) appear to be positive. Ageing infrastructure, worsening road congestion, crowded public transport and urban sprawl all feature prominently among the issues identified in the literature (Schrank et al., 2019; Infrastructure Australia, 2019). These phenomena foster concerns about the growing levels of stress experienced by commuters, and the knock-on effects on their mental and physical health (Flood and Barbatto, 2005). Among the measures proposed to counter the rise of commuting times and improve workers' outcomes, working-from-home (WFH) arrangements have gained a distinct prominence. To wit, proponents argue that WFH arrangements can induce sizable improvements in workers' mental health, wellbeing, and overall productivity (Productivity Commission, 2021).

However, whether these claims are justified remains an open question, and a subject of keen academic interest. A small—yet influential—literature has investigated the effects of commuting on mental health outcomes. Several studies leveraging panel-data models have shown that increases in commuting time lead to poorer mental health outcomes, in particular among women (Roberts et al., 2011; Jacob et al., 2019; Clark et al., 2020). Other studies have linked commuting and transport congestion to lower wellbeing and negative psychological costs (Gottholmseder et al., 2009; Anderson et al., 2016; Beland and Brent, 2018).

The literature on the effects of WFH is less conclusive. A large body of interdisciplinary work has examined the link between WFH and subjective wellbeing, but it did not reach a consensus (Bailey and Kurland, 2002; Gajendran and Harrison, 2007). Recent experimental studies conducted within companies found positive effects of WFH on wellbeing (Bloom et al., 2015; Mas and Pallais, 2017), whereas early empirical studies of the massive rise of WFH due to the COVID-19 pandemic yielded negative effects, especially among women (Lyttelton et al., 2020; Xiao et al., 2021).[1]

[1] The lack of consensus in the WFH literature may be attributable to differences in research designs. The interdisciplinary studies are mostly correlational and therefore unlikely to yield causal effects. Similarly, the effects of WFH during the COVID-19 pandemic may be confounded by the unfolding health crisis, mobility restrictions, or school closures (Etheridge et al., 2020; Barrero et al., 2021; Gibbs et al., 2021). The experimental designs should be absent of such confounders, but the idiosyncrasies of firms that carried out the experiments may limit the external validity and comparability of the resulting findings with the rest of the literature.

In this study, we investigate the causal effects of commuting and WFH arrangements on the mental health of Australian men and women. We do so in a single empirical design, which allows us to determine whether WFH affects people's mental health *per se*, or whether the effects are attributable to the associated reductions in commuting time. Following in the tradition of panel-data models first estimated by Roberts et al. (2011), we use a nationally representative longitudinal household survey to minimize the contextual specificity of our findings, and we carefully leverage within-person variation in commuting times and WFH arrangements to account for potential confounders. We restrict our analysis to the period 2002-2019, thereby avoiding the confounding factors affecting both mental health and the WFH take-up in the wake of the COVID-19 pandemic. Notably, we extend the original modelling framework of Roberts et al. (2011) by operationalizing the Unconditional Quantile Regression (UQR) models (Firpo et al., 2009; Rios-Avila, 2020). This allows us to determine whether the uncovered effects are contingent on people's baseline levels of mental health.

Our results indicate that commuting time does not affect the mental health of Australian women. For Australian men, we find small negative effects that manifest among men with below-median levels of mental health. These results are important, since previous research using British subjects found that commuting time has a larger negative effect on women, and no effect on men. Next, we show that WFH arrangements have a positive effect on Australian women, with the largest benefits experienced by women below the 30th quantile of the mental health distribution. We also show that these benefits manifest only at higher WFH intensities, with the largest effects experienced by women who work mainly from home whilst retaining a fractional office/on-site presence. For men, we do not find any positive effects of WFH arrangements. To investigate whether the observed contingency of mental health effects extends beyond Australia, we estimate the UQR models on a British sample (generously provided by Jacob et al., 2019), confirming that the negative effects of commuting time on British women are also attributable to women with low baseline levels of mental health.

We contribute to the literature in several substantive ways. To the best of our knowledge, ours is the first study to apply Roberts et al.'s (2011) modelling framework to study the causal effects of WFH arrangements, and the first study to disentangle the intrinsic effects of WFH arrangements from the associated changes in commuting patterns. Drawing on a nationally representative dataset, we produce findings that are characterized by high degrees of precision and external validity. From the methodological perspective, our use of UQR models provides novel insights into the mechanisms underlying the established mental health effects. In this respect, we build on the medical literature indicating that responses to stressors are more pronounced among people with relatively poor levels of mental wellbeing (Schiele and Schmitz, 2016; Zorn et al., 2017). We are also the first study to study the effects of commuting time on mental health outside the UK, providing a valuable counterfactual to the existing scholarship (Roberts et al., 2011; Jacob et al., 2019; Clark et al., 2020).

Australia presents a particularly interesting case in this regard, being a country with rapidly growing urban population, strained transport infrastructure, and a strong upward trend in commuting times (see Figure 1a). The Australian context is also well-suited for evaluating the effects of WFH arrangements, since the share of Australian employees working from home (Figure 1b) has been historically larger than in most OECD countries (Milasi et al., 2021; Wilkins et al., 2022). Australia is also more comparable to the U.S. and Canada, being characterized by lower development densities, more dispersed populations, and a car-centric transport culture. We further note that Australia is tackling systemic problems with access to mental health services (Productivity Commission, 2020), which heightens the importance of research into the drivers of mental health among its populace.

The rest of the paper is organised as follows: Section 2 presents an overview of the relevant literature. Section 3 outlines the HILDA data, the construction of our analytical sample, and descriptive statistics. Section 4 provides details of our empirical strategy. Section 5 discusses the results. Section 6 summarizes the robustness checks. Section 7 discusses the implications of our study and comments on the reasons why some of our findings deviate from the existing UK-based scholarship.

FIGURE 1A: AVERAGE ONE-WAY COMMUTING TIMES OF AUSTRALIAN EMPLOYEES, 2002-2019

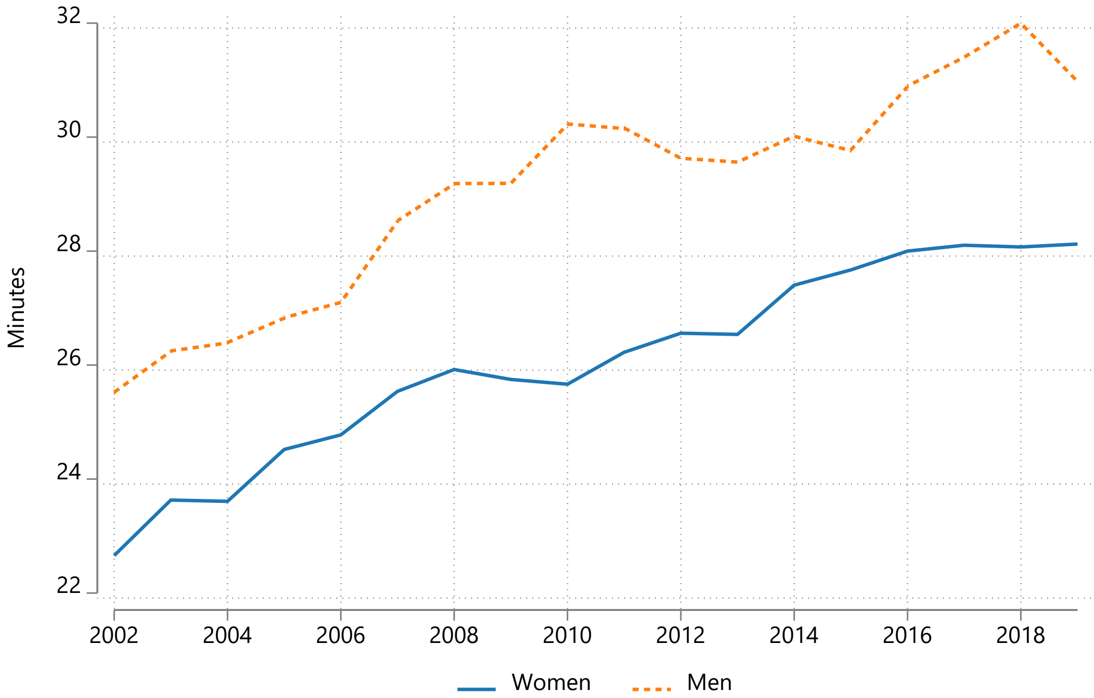
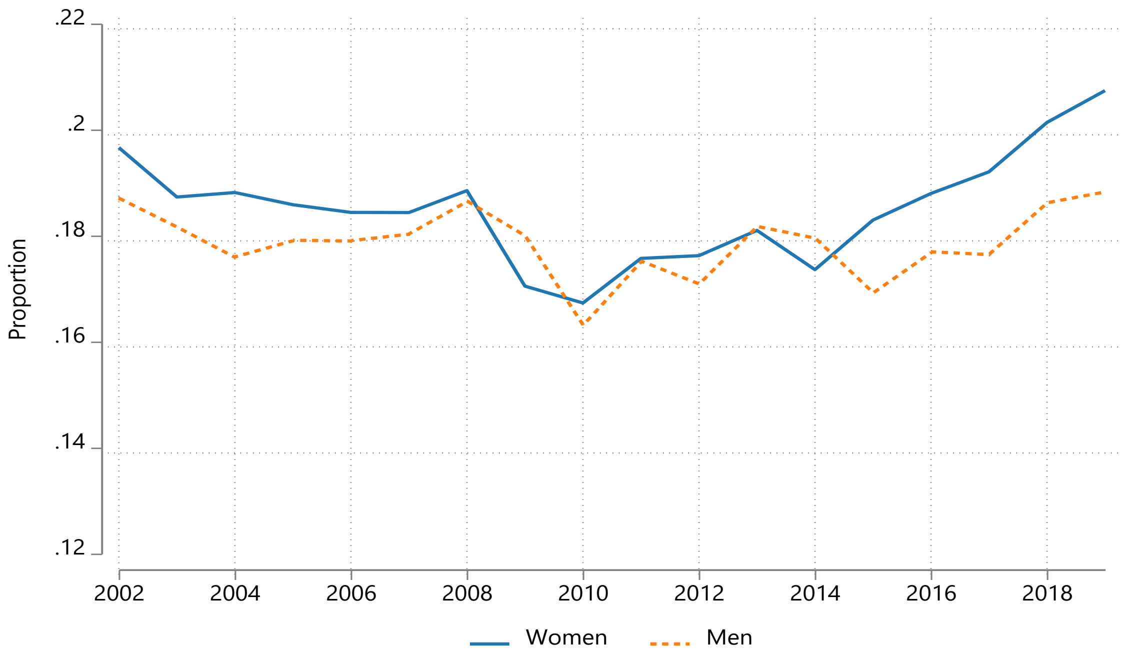


FIGURE 1B: SHARE OF AUSTRALIAN EMPLOYEES WORKING FROM HOME, 2002-2019



Notes: Figure 1a shows average daily one-way commuting times between home and work, derived from reported weekly commute time and days worked per week. Figure 1b shows the mean proportion of employees working any weekly working hours from home. Source: Household, Income and Labour Dynamics in Australia (HILDA) Survey.

2. LITERATURE

2.1. Literature on commuting

There is a well-established literature studying the link between commuting and various psychological outcomes, including subjective wellbeing, overall life satisfaction and mental health. Early explorations of these themes include Redmond and Mokhtarian (2001), who investigated the association between ideal (preferred) commuting times and actual commuting frequencies, finding that ideal commuting times decrease with the frequency of commuting, and Kahneman (2006), who showed that people considered commuting to be the least enjoyable part of their daily routines.

These exploratory studies were followed by Stutzer and Frey (2008) who used the German Socio-Economic Panel (SOEP) to investigate whether commuting distance affects life satisfaction. The main result of their analysis was that people living farther from their workplace are worse off than those living closer. Lorenz (2018) assessed a more recent release of the SOEP data, finding that commuting distance does not affect life satisfaction *per se*, but it does affect subdomains of life satisfaction, namely satisfaction with family life and with leisure. Künn-Nelen (2016) expanded the focus to physical health: using data from the BHPS and UKHLS, she showed that longer commuting times decrease workers' satisfaction with their health, although she did not find significant effects on objective measures of workers' health.

Longitudinal studies focusing on the explicit link between commuting and mental health started with Roberts et al. (2011), who used the first 14 waves of the BHPS data (1991-2004) to show that longer commuting time lowers the GHQ-12 mental health score of women, but not that of men. Jacob et al. (2019) used UKHLS data for the period 2009 to 2016 to evaluate the effects of both commuting times and commuting modes. The authors replicated the findings of Roberts et al. (2011), and they also found that commuting by bus and as a passenger in a car are not as detrimental to people's mental health as other forms of commuting.

Clark et al. (2020) used the UKHLS data to investigate the links between the commuting time, commuting mode, and various outcomes of interest, including mental health, life satisfaction and other domains of wellbeing. Using a correlated random effects model (CRE), the authors found a significant effect of commuting time on mental health of men and women (estimated jointly), although the magnitude of this effect was smaller than that of Roberts et al. (2011) and Jacob et al. (2019). Furthermore, the effect became statistically insignificant in a person fixed-effects specification of the model. Consistent with Jacob et al. (2019), the authors also found commuting by bus to be preferable to other forms of commuting.

In Table 1, we present an overview of the key characteristics and findings of the studies of commuting time and mental health, accompanied by their effect size estimates for both men and women. Note that the original published estimates have been re-scaled and normalized, so that they represent the effects of increasing one-way commute by one minute, measured in terms of standard deviations (SD) of the GHQ-12 mental health score.

TABLE 1. PREVIOUS ESTIMATES OF THE EFFECT OF COMMUTING TIME ON MENTAL HEALTH

	Dataset and sample period	Method	Number of observations (individuals)	Standardized estimates	
				Men	Women
Roberts et al. (2011)	BHPS 1991-2004	FE	69,045 (15,000)	-0.0004	**-0.0015**
Jacob et al. (2019)	UKHLS 2009-2014	FE	56,635 (15,846)	0.0000	**-0.0016**
Clark et al. (2020)	UKHLS 2009-2015	CRE	79,577 (26,498)	**-0.0006**	
Clark et al. (2020)	UKHLS 2009-2015	FE	N/A (26,514)	-0.0005	-0.0001

Notes: Standardised estimates represent the effect of raising one-way commuting time by one minute in terms of standard deviations of the GHQ-12 mental health score. Estimates in bold typeface are statistically significant at the 95% confidence level. FE – Fixed Effects; CRE – Correlated Random Effects.

There are several key takeaways from Table 1. First, we note that the effect magnitudes are relatively modest. The strongest effects were found by Jacob et al. (2019), whose estimates imply that increasing a one-way commute by 30 minutes results in a 0.048 SD decline of women's mental health score. The effects reported by Clark et al. (2020) are considerably weaker, and the lack of significant effects corresponding to their FE model specification is potentially concerning (since theirs is the largest study using the FE design).

Second, the empirical evidence summarized in Table 1 is specific to one country (the United Kingdom), and two closely related survey datasets (BHPS and UKHLS). While this feature has the advantage of helping us assess the sensitivity of the presented findings, it also raises questions regarding the potential idiosyncrasies of the data and the broader national context. Indeed, we may be concerned that these findings may not translate to other datasets and countries. To this end, empirical studies using data from other countries are likely to be particularly beneficial.

Third, all the studies listed in Table 1 have tested for average effects of commuting time on mental health, implicitly assuming that the effect of commuting on mental health is the same for individuals across the entire mental health distribution. However, it is possible that the effects of commuting time vary depending on a person's initial or 'baseline' level of mental health. Existing work has indeed demonstrated that mental health effects of, for example, job loss (Schiele and Schmitz, 2016), housing affordability (Baker et al., 2020), conditional cash transfers (Ohrnberger et al., 2020), and child labour (Jayawardana et al., 2023) are largest for people in the middle to lower parts of the mental health distribution. Given evidence of such distributional effects in other contexts, we provide the first investigation of whether the effects of commuting time on mental health also depend on individuals' baseline levels of mental health.

2.2. Literature on working from home arrangements

There is an established interdisciplinary literature that investigates the associations between WFH arrangements and people's psychological and employment outcomes. A meta-analysis by Bailey and Kurland (2002) yielded no evidence of a positive association between WFH arrangements and job satisfaction or productivity. Another meta-analysis by Gajendran and Harrison (2007) indicated existence of small positive associations between WFH arrangements and various psycho-social outcomes, but the authors note high variability of the studied estimates. This raises the possibility that the effects of WFH arrangements have high contextual and institutional specificity. The authors also acknowledge that the surveyed findings may not be indicative of causal effects, because the decision to commence working from home is often accompanied by other confounding changes to respondents' lives (*e.g.*, job changes, residential moves, or changes in caregiving obligations).

The COVID-19 pandemic has led to a surge of interest in the impacts of WFH arrangements on workers' wellbeing, and there are several studies reporting on the experiences of workers who found themselves working from home during the pandemic. Lyttelton et al. (2020) analysed the COVID Impact survey, showing that American parents working from home during the pandemic did not differ from parents working on-site in terms of their reported levels of subjective wellbeing. The authors also showed that mothers working from home reported heightened feelings of anxiety relative to fathers working from home. Xiao et al. (2021) analysed a convenience sample of (primarily American) respondents to an online questionnaire, showing that the respondents who transitioned to WFH arrangements have developed a range of physical and mental health issues. However, even these studies are unlikely to yield the causal effects of WFH arrangements because it is difficult to disentangle the effects of WFH from those of the unfolding health crisis (Gibbs et al., 2021; Etheridge et al., 2020; Barrero et al., 2021).

The causal effects of WFH arrangements have been explored by two experimental studies that were conducted in collaboration with private-sector partners. Bloom et al. (2015) partnered with a Chinese travel agency to administer a randomized control trial on their call-center workforce. The workers who expressed interest in WFH were randomly assigned into treatment that involved working 4 days per week from home and 1 day per week from the office (with the control group working 5 days per week from the office). The treatment group displayed a range of positive effects, including higher job and life satisfaction, less exhaustion, and higher productivity. Notably, the authors theorized that the reductions in commuting time are likely to play an important role in mediating the observed WFH effects. Mas and Pallais (2017) administered a discrete choice experiment in an American call center, eliciting workers' willingness to pay for WFH, among other alternative work arrangements. This study revealed that workers are willing to give up 8 percent of their wages for the option to work from home. The authors concluded that the availability of WFH is likely to improve workers' welfare and satisfaction levels.

Despite the high degree of institutional and contextual specificity of the two experimental studies, their findings raise the possibility that the positive causal effects of WFH extend to broader populations and translate to other outcomes as well. Investigating whether this is indeed the case is the next logical step for the WFH literature.

3. DATA

We use data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, spanning the period 2002 to 2019. The HILDA Survey is an annually conducted longitudinal socio-economic survey that follows a representative sample of approximately 7,500 Australian households, interviewing all household members aged 15 and over.[2]

Commuting time is captured by the question: "How much time would you spend on each of the following activities in a <u>typical</u> week?" with one of the activities listed being "<u>travelling to</u>

[2] Annual re-interview rates are high, rising from 87% in Wave 2 to 96% by Wave 9 and remaining above that in Waves 10 to 19 (Summerfield et al., 2020).

and from a place of paid employment.” Respondents are asked to provide the number of hours and/or minutes. To make our measure of commuting more comparable with the existing studies, we combine this information with the reported usual number of days worked per week to derive a measure of daily one-way commuting time (expressed in minutes).

For our WFH measure we use information on reported hours usually worked from home in the main job per week. We calculate the share of all working hours worked at home based on reported usual hours of work in the main job, and we split the responses into four categories (less than 25%, 25-50%, 50-75%, 75% and more), with the omitted category being ‘no WFH’. We have opted to use a set of dummies (as opposed to a continuous variable), because it allows us to capture potential non-linearities in the relationship between the intensity of WFH arrangements and mental health.

Our measure of mental health is the five-item Mental Health Inventory (MHI-5) derived from the Short-Form (SF-36) Health Survey (Ware et al., 2000). Respondents are asked “How much of the time during the past 4 weeks:” (i) “have you been a nervous person?”, (ii) “have you felt so down in the dumps that nothing could cheer you up?”, (iii) “have you felt calm and peaceful?”, (iv) “have you felt down?”, and (v) “have you been a happy person?”.[3] For each item, response options range from 1 (‘all of the time’) to 6 (‘none of the time’). Responses to these items are transformed to a scale ranging from 0-100, with higher values reflecting better mental health (see Bubonya et al., 2019). Evidence has demonstrated substantial agreement between the MHI-5 and GHQ-12 responses (Hoeymans et al., 2004; Elovanio et al., 2020), which means that reasonable comparisons can be made between our results using the MHI-5 and the results of previous studies using the GHQ-12.

Control variables have been selected based on the variables used by Roberts et al. (2011). These include respondents’ demographic characteristics, socio-economic status, employment characteristics and selected subjective assessments.[4] Appendix Table A1 lists the definitions of all the variables. Another similarity to Roberts et al. (2011) is that we use residential and work histories to identify the instances when workers changed jobs or relocated to a different

[3] The five items included in the MHI-5 measure are part of a nine-item question. The remaining items that are not used to construct the MHI-5 measure are: ‘did you feel full of life?’; ‘did you have a lot of energy?’; ‘did you feel worn out?’ and ‘did you feel tired?’.
[4] The subjective assessments are self-rated health, neighbourhood satisfaction, and job satisfaction. Given that these may constitute potential collider variables, we also estimate an alternative specification that excludes these controls.

home. Identifying these events allows us to define home-job spells for the panel data models that are central to our analysis.

Our analysis sample is subject to several sample restrictions. First, we exclude respondents who are aged below 18 years or above 64 years. Second, we exclude respondents who do not work (and hence do not commute). Third, we exclude workers who are self-employed (because they tend to have irregular commuting patterns and work locations). Fourth, we exclude respondents who are not observed to work for the same employer for at least two consecutive years. The resulting unbalanced panel contains 16,357 unique employees with 114,902 employee-year observations.

Table 2 presents summary descriptive statistics of all variables that enter our model. The average one-way commuting time is 27.08 minutes for women and 30.45 minutes for men, which is somewhat higher than the average times reported for the UK.[5] This is consistent with Meekes's (2022) observation that Australian cities are more likely to be monocentric, having a greater proportion of commutes to a single central business district, and being subject to greater transport congestion. With respect to WFH arrangements, we see that 17.95% of women and 17.23% of men work at least partially from home. Among these women and men, the average shares of hours worked from home are 24.03% and 17.23%, respectively.

[5] Roberts et al. (2011) report 20.78 and 24.65 minutes for women and men, respectively, while Jacob et al. (2019) report 23.62 and 27.83 minutes for women and men, respectively.

TABLE 2: SUMMARY STATISTICS OF THE ANALYSIS SAMPLE

	Women		Men	
	Sample mean	Standard deviation	Sample mean	Standard deviation
Age	38.66	12.43	38.40	12.30
Commuting time *(one-way, in minutes)*	27.08	24.33	30.45	25.24
Working (fully or partially) from home *(%)*	17.95		17.23	
Share of total hours WFH *(conditional on WFH)*	24.03	24.21	18.95	20.02
Mental health *(0-100 score)*	73.53	16.42	75.80	15.56
Self-rated health *(5-point scale)*	3.57	0.86	3.58	0.87
Marital status (%)				
Married	47.82		50.30	
In a *de facto* relationship	14.20		13.77	
Separated	2.97		1.86	
Divorced	6.75		3.23	
Widowed	1.03		0.27	
Never married and not de facto	27.24		30.57	
Educational attainment (%)				
Master's or doctorate degree	6.01		7.05	
Graduate diploma or graduate certificate	7.77		5.42	
Bachelor's degree	21.68		16.47	
Diploma or advanced diploma	11.18		8.87	
Certificate III or IV	16.25		27.29	
Finished year 12	19.24		18.64	
Finished year 11 or less	17.87		16.01	
Children characteristics (%)				
Has children aged 0-4 years	11.76		16.01	
Has children aged 5-9 years	13.38		13.77	
Has children aged 10-14 years	15.15		13.41	
Employment and income				
Hourly wage rate *(AUD)*	30.33	14.15	35.27	17.61
Weekly working hours	32.72	12.81	41.28	11.75
Log household annual income	10.93	0.57	10.92	0.58
Satisfaction with living and work arrangements				
Neighbourhood satisfaction *(11-point scale)*	7.82	1.63	7.77	1.59
Job satisfaction *(11-point scale)*	7.64	1.64	7.54	1.62
Number of observations	58,217		55,809	

Notes: Data from HILDA Survey, 2002-2019. An individual in the analysis sample contributes an observation in every year they are recorded as an employee aged 18 to 64.

4. Analytical Methods

To identify the effects of commuting time and working from home on mental health outcomes, we use panel data models that leverage within-person variation in respondents' commuting times and working arrangements. We rely on fixed-effects models that account for the confounding influences of people's time-invariant unobservable characteristics (such as latent abilities, genetic predispositions, or personality traits).

Yet, even within-person variation in commuting times can be endogenous, especially if it is caused by other major life events (such as home relocations or job changes). For this reason, Jacob et al. (2019) restrict their sample to individuals who have not moved residence and have not changed job or employer within the entire period of observation (the same restriction is imposed in a robustness check performed by Roberts et al., 2011).[6] One potential drawback of such a restriction is that it is likely to yield a selective sample of relatively immobile individuals who are both working for the same employer and living in the same residence for a long period of time (18 years in our case). To address this selectivity, we keep mobile individuals in the sample and instead split their observations into unique home-job spells. If an individual changes their residential address or their job, this marks the start of a new home-job spell. It is then *within* these individual home-job spells that we examine the effects of changes in commuting time and WFH arrangements.

Consequently, any changes to commuting time and WFH arrangements are orthogonal to these major life events, are likely driven by exogenous factors such as changes to road congestion, public transport capacity, population density, or other aspects of commuting infrastructure (Roberts et al., 2011).

Note that other life events that may jointly affect commuting times and mental health, such as childbearing or marriage, enter our model as controls. For completeness, we also estimate and report the results corresponding to the model that implements the original restrictions of Roberts et al. (2011) and Jacob et al. (2019).

We first estimate linear fixed-effects regression models that let mental health be a function of commuting time, WFH arrangements, other time-variant controls, time-invariant fixed effects, and an error term. The functional form is:

[6] Jacob et al. (2019) imposed two additional restrictions: they exclude individuals who are not employed in some years; and they exclude individuals who never experience a change in commuting time from one year to the next of at least five minutes.

$$y_{it} = \beta \cdot C_{it} + \boldsymbol{\gamma} \cdot \mathbf{W}_{it} + \boldsymbol{\delta} \cdot \mathbf{X}_{it} + \nu_i + \varepsilon_{it}, \tag{1}$$

where subscript i refers to the unique home-job-individual identifier and subscript t refers to the year of observation. The variable y_{it} is our measure of mental health, C_{it} is one-way daily commuting time, $\mathbf{W}_{it}$ is the set of WFH dummies, $\mathbf{X}_{it}$ is a vector of time-variant control variables, ν_i denotes the home-job-individual fixed effects, and ε_{it} is the error term. For the sake of comparability, we standardize the mental health outcomes to have a mean of zero and a standard deviation of one. The key parameters of interest are β and $\boldsymbol{\gamma}$, which represent the average causal effects of commuting time and WFH intensity on respondents' mental health. Unless stated otherwise, throughout the manuscript we cluster standard errors at the individual home-job spell level.

After estimating the average causal effects, we turn our attention to effect heterogeneity, evaluating whether the causal effects are contingent on the respondent's baseline level of mental health. To this end, we estimate a fixed-effects version of Firpo et al.'s (2009) unconditional quantile regression (UQR).[7] This estimation method relies on the concept of the recentered influence function (RIF), which essentially reweights the outcome variable so that its mean corresponds to the quantile of interest. The regression model is then applied directly to the reweighted outcome, using the same home-job-individual fixed effects as the baseline specification. The advantage of this approach is that it allows us to proceed quantile-by-quantile and assess whether people at the lower end of the mental health distribution respond to commuting times differently than people at its higher end.[8]

[7] The UQR model has been applied in many different contexts, such as in the study of medication adherence (Borah and Basu, 2013), savings and locus of control (Cobb-Clark et al., 2016), adolescent health (Atkins et al., 2020), financial wellbeing (Botha et al., 2021), and socioeconomic health gradients (Sinha et al., 2021). For details regarding the implementation of the fixed-effects UQR model, see Rios-Avila (2020).

[8] In addition to allowing us to estimate the causal effects at various points of the mental health distribution, unconditional quantile regression retains the conventional advantages of quantile regression. Specifically, distribution quantiles are invariant to monotonic transformations of the dependent variable, which is convenient for constructed survey items such as mental health scores (since the distributional profile of these variables is heavily dependent on the nature of questions asked, and therefore largely arbitrary).

Following Firpo et al. (2009), we define the influence function (IF) for each quantile τ of the distribution of mental health, y_{it}:

$$\text{IF}(y_{it};q_\tau)=\left(\tau-\mathbf{1}\left[y_{it}\le q_\tau\right]\right)\big/f_y(q_\tau), \tag{2}$$

where q_τ is the value of the cumulative distribution of mental health (y_{it}) at τ-th quantile, and $f_y(\cdot)$ is the marginal density function of y_{it}.

The RIF function then recenters the influence function so that its mean corresponds to the cumulative distribution value at the quantile of interest:

$$\text{RIF}(y_{it};q_\tau)=\text{IF}(y_{it};q_\tau)+q_\tau \tag{3}$$

The expectation of the RIF is estimated conditional on the same set of explanatory variables and fixed effects as in Equation 1:

$$E\left(\text{RIF}(y_{it};q_\tau)\middle|X_{it}\right)=\beta\cdot C_{it}+\boldsymbol{\gamma}\cdot\mathbf{W}_{it}+\boldsymbol{\delta}\cdot\mathbf{X}_{it}+\nu_i+\varepsilon_{it} \tag{4}$$

The key parameters of interests are again β and $\boldsymbol{\gamma}$. Parameter β denotes the marginal change in the value of the quantile associated with a one-minute increase of the unconditional average of the distribution of commuting time (*i.e.*, $\Delta\overline{C}_{it}=1$). Parameters $\boldsymbol{\gamma}$ denote the change in the value of the quantile associated with a switch from no WFH arrangement to the respective WFH intensity.

5. RESULTS

5.1. Linear regression results

The key coefficient estimates corresponding to the linear fixed-effects regression models are presented in Table 3 (while detailed results can be found in Appendix Table A2). Column 1 lists the coefficients corresponding to the baseline model that does not distinguish between men and women. The coefficient on commuting time is -0.0002, which is quantitatively small[9] and not significantly different from zero (p = 0.202). When compared to the estimates listed in Table 1, our estimate is an order of magnitude lower than (and significantly different from) the fixed effect estimates of Roberts et al. (2011) and Jacob et al. (2019). The coefficients on WFH intensity show that the first two regimens (with WFH components accounting for less than 50%

[9] If we were to take the insignificant estimate at it's a face value, a 30-minute increase in one-way commuting time would be predicted to cause a 0.0062 SD decrease of the mental health score.

of work hours) are virtually indistinguishable from the reference regimen of no WFH. The coefficients on work regimens with higher WFH components are positive and larger in magnitude, however they are also not statistically significant at the conventional confidence levels.

Next, we estimate the fixed-effects models separately for each gender. The coefficients on commuting time mirror the pooled specification. This means that commuting time is not a strong driver of mental wellbeing among Australian men and women. Regarding WFH intensity, the models once again yield null results for WFH components accounting for less than 50% of work hours. For women, we observe that working 50-75% of their work hours from home yields mental health scores that are 0.08 SD higher than the baseline ($p = 0.047$) and working 75% or more yields an increase of 0.04 SD, although the latter is not statistically significant. For men, we do not see any positive effect corresponding to WFH intensity of 50-75%, and an insignificant positive effect (0.04 SD) for the highest WFH intensity.

TABLE 3: ESTIMATES OF THE EFFECTS OF COMMUTING TIME ON MENTAL HEALTH – BASELINE FIXED-EFFECTS MODEL

	(1) All	(3) Women	(4) Men
Commuting time *(one-way, in minutes)*	-0.0002 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
Share of hours WFH (*reference category: no WFH*)			
0% < Share < 25%	-0.0072 (0.0004)	-0.0145 (0.0136)	0.0005 (0.0132)
25% ≤ Share < 50%	0.0004 (0.0170)	-0.0028 (0.0218)	0.0042 (0.0272)
50% ≤ Share < 75%	0.0458 (0.0303)	0.0805** (0.0405)	-0.0091 (0.0435)
Share ≥ 75%	0.0397 (0.0350)	0.0396 (0.0458)	0.0433 (0.0527)
Number of observations	113,467	57,963	55,504
Number of home-job spells	47,076	24,000	23,076
R-squared	0.0622	0.0640	0.0619

Notes: Robust standard errors, clustered at the home-job-spell level, are in parentheses. ** $p < 0.05$. Full results are shown in Table A2. All models include controls for age, self-rated health, marital status, log of equivalized household disposable income, weekly wage rate, education, presence of children, working hours, neighborhood satisfaction, job satisfaction, and year dummies.

These results suggest that working from home may indeed prove beneficial for the mental health of women, while having no significant impact on men. The most beneficial regimen (for women) consists of working mainly from home but keeping a moderate presence at the workplace. Notably, this regimen echoes the experimental design of Bloom et al. (2015), who also offered their subjects a mixed allocation of WFH combined with a moderate amount of work in the office.

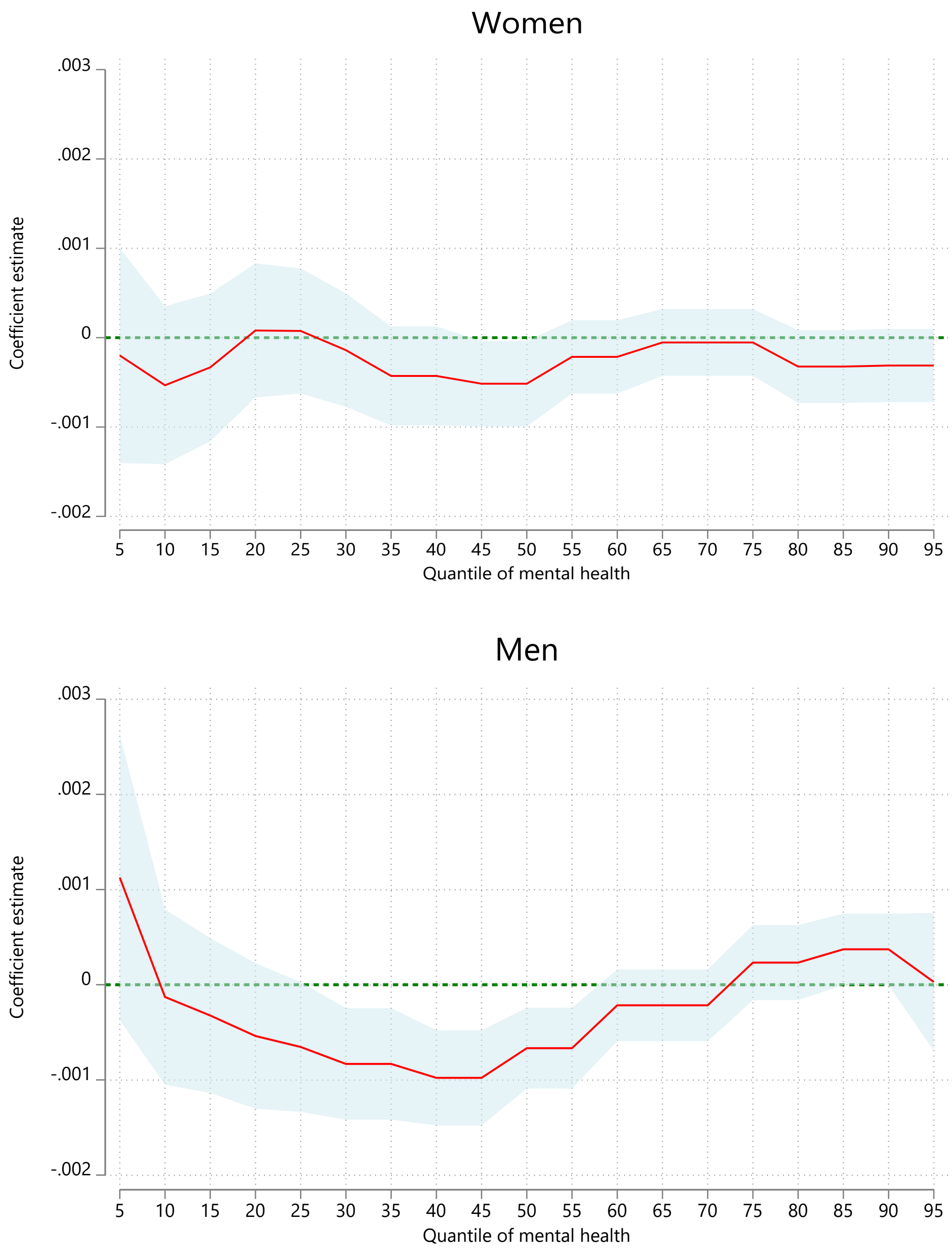
5.2. Unconditional quantile regression results

The results presented in the previous section suggest that, on average, commuting time does not affect the mental health of Australian employees. However, these null average effects may be concealing important heterogeneities. Intuitively, it is possible that commuting time affects people with poor mental health differently than people whose mental health is good, and similar differences may also underly the effects of WFH arrangements. Our unconditional quantile regressions allow us to explore these possibilities.

The main UQR results are presented graphically in Figures 2 and 3, which plot the magnitudes of causal effects of commuting time and WFH arrangements conditional on the baseline level of respondents' mental health.[10] Starting with commuting time, Figure 2 indicates that an exogenous increase in commuting time has no negative impact on women across the entire mental health distribution. In contrast, the results for men show a clear dependence on men's position within the mental health distribution. Negative effects of commuting time are concentrated among men with below-median levels of mental health, with the strongest effects manifesting between the 40th and 45th quantiles of the mental health distribution. Within this range, a 1-minute increase of one-way commuting time lowers the respondents' mental health score by 0.001 SD. For a 30-minute increase, the effect is 0.03 SD, which is comparable to the effect of raising the respondents' household income by 2%.

[10] UQR plots for a pooled sample of women and men can be found in Appendix Figures A1 and A2. Detailed results can be found in Appendix Tables A6-A8.

FIGURE 2: UNCONDITIONAL QUANTILE REGRESSION RESULTS—THE EFFECTS OF COMMUTING TIME ON MENTAL HEALTH BY GENDER



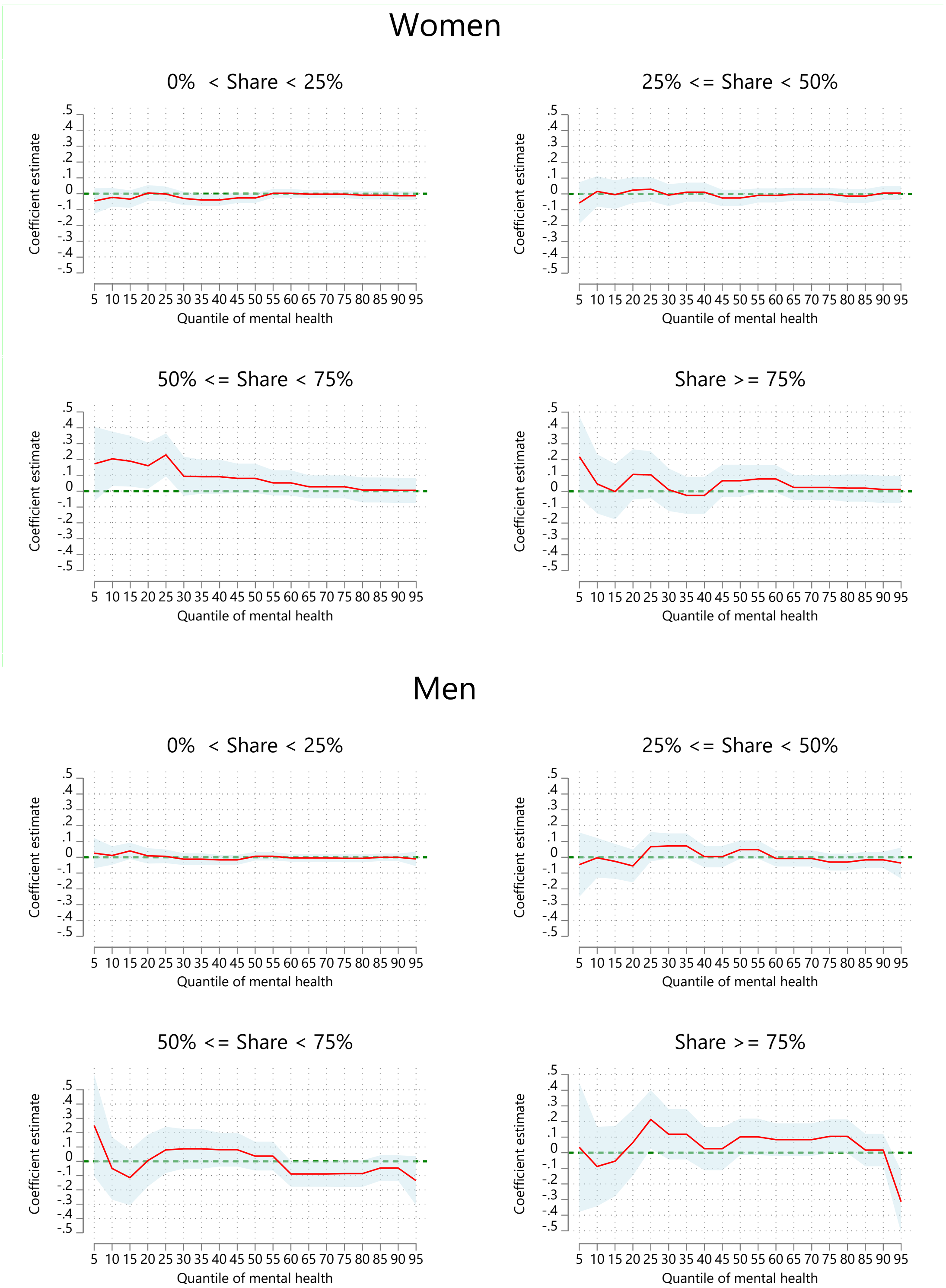
Notes: The figure presents the estimated UQR coefficients for one-way daily commuting time (in minutes) at distinct quantiles of the mental health distribution. The dependent variable is our standardised MHI-5 measure of mental health. Shaded region represents the 90% confidence intervals. Data from HILDA Survey, 2002-2019.

Figure 3 plots the UQR results for the intensity of WFH arrangements. The results for women show that the significant positive effect of working 50-75% of work hours from home is attributable primarily to women with low levels of mental health, being particularly pronounced among those below the 30th quantile of the mental health distribution. For these women, working mostly from home increases the mental health score by approximately 0.2 SD, which is a large effect that is comparable to raising their household income by 15%. In contrast, the UQR results for the other WFH intensities fail to yield a clear dependence of the effect magnitudes on the women's position in the mental health distribution. The results for men are similarly inconclusive; there is suggestive evidence that working 75% or more work hours from home is beneficial for a large array of men (between the 25th and 80th quantile of the mental health distribution), however—similar to the baseline FE model—these coefficients fail to attain statistical significance.

Altogether, the UQR analysis reveals that the significant effects of commuting time and WFH arrangements on mental health are concentrated among people with relatively low baseline levels of mental health. In order to assess whether this dependence is unique to the Australian context, we have applied our UQR model also to the UK data analysed by previous commuting studies.[11] The analysis (presented in Appendix A1) reveals that the UK findings are also driven by people at the low end of the mental health distribution, which bolsters the external validity of our findings and highlights the specificity of the presented effects.

[11] We thank Nikita Jacob for generously sharing with us the code that generates the analytical sample used in Jacob et al. (2019).

FIGURE 3: UQR RESULTS—THE EFFECTS OF WFH INTENSITY ON MENTAL HEALTH BY GENDER



Notes: Estimated UQR coefficients for shares of total weekly working hours that are worked from home at each quantile of the mental health distribution, relative to individuals who do not work from home. The dependent variable is a standardised MHI-5 measure of mental health. Shaded region represents the 90% confidence intervals. Data from HILDA Survey, 2002-2019.

6. ROBUSTNESS CHECKS

We conducted several robustness and sensitivity checks to ensure that our results are valid. First, we find that our results are robust to using the more stringent sample restrictions of Jacob et al. (2019) and including individual fixed effects instead of home-job-individual fixed effects (see Appendix Table A3). The 50-75% WFH coefficient did not attain statistical significance in the linear fixed-effects model, but the UQR results remain indicative of a positive effect among women with low baseline levels of mental health. At the same time, it is worth emphasizing that this model uses a much more selective sample of individuals who neither changed job nor moved home during the entire observation period. The resulting loss of observations (32% of the principal sample), and changes to the sample composition should be taken into account when interpreting the corresponding results.

Second, to assess the presence of non-linearities in the effect of commuting, we estimated a fixed-effects model specification with an added quadratic term for commuting time. The quadratic term did not prove statistically significant (Table A4), and the practical implications of the model were unaffected by this addition.

Third, we re-estimated all models excluding self-rated health as a control. This is because self-rated health could be endogenous to mental health (Roberts et al., 2011). The results of this robustness check (available upon request) proved very similar to our main findings and did not change any of the presented conclusions.

Fourth, we explored the issue of selection into employment. As noted by Roberts et al. (2011), we only observe commuting time among those respondents who are employed at the time of the survey. Thus, we are unable to capture what would be the commuting time responses of non-employed respondents. Indeed, it may be the case that the people who experience the worst mental health effects of commuting prefer not to be employed. Following Roberts et al. (2011), we estimated Heckman selection models of the probability of being employed. The non-selection hazard ratio (or inverse Mills ratio) generated from these models was then included as an additional covariate in the model that explains mental health (overall average effects model). The coefficient on the non-selection hazard ratio was almost always negative and significant (similar to Roberts et al.'s finding), which suggests that our estimates of commuting time on mental health constitute the lower bound of the effects applicable for the full population. These results are not reported here (because inclusion of the non-selection hazard ratio makes no difference to our main findings), but they are available upon request.

Finally, we assessed whether the dependence of causal effects on respondents' baseline levels of mental health that we find can be explained by omitted variables that jointly affect respondents' mental health and its sensitivity to commuting times and WFH arrangements. To this end, we estimated series of unconditional quantile models, in which we selectively excluded various control variables (thereby creating omitted variables) and assessed the stability of the respective UQR patterns. The excluded variables are: household income, wage rate, self-rated health, working hours, and children controls. The UQR patterns were not sensitive to these exclusions, suggesting it is indeed low mental health *per se* that is driving the observed differences in unconditional quantile results.

7. Discussion and Conclusion

In this study, we have estimated causal effects of commuting time and work-from-home arrangements on the mental health of Australian men and women. The identification was aided by panel-data models with individual home-job fixed effects, which allow us to identify and isolate shocks that are unrelated to major life events, such as job changes or home relocations.

Starting with commuting time, our analyses yield no evidence of adverse effects on the mental health of Australian women. For men, we find effects that are contingent on their baseline level of mental health. Those with below-median levels are negatively affected by commuting time, whereas those with above-median levels are not. This contrasts with previous research, which reported relatively large negative effects for British women, and no effects for British men. Our unconditional effect estimates are quantitatively small (being an order of magnitude smaller than the unconditional estimates for British women). This suggests that, in Australia, commuting time is not as strong a determinant of mental wellbeing as it is in the UK.

In light of these results, it is natural to ask why the Australian setting gives rise to a gendered pattern that is opposite to the one found earlier in the UK. One explanation relates to the availability and affordability of childcare. Australian urban areas are characterized by a well-developed formal childcare sector that is heavily subsidized by the state and federal governments.[12] The ease of access to the formal childcare services and their lower out-of-pocket costs may well be attenuating the adverse effects of commuting time on the mental

[12] The OECD reports that, between 2004 and 2015, the out-of-pocket costs of full-time formal childcare for an Australian couple with two pre-school children and average wages amounted to 12-14% of their income. For an equivalent British couple, these costs amounted to 24-31% of their income (for details, see OECD, 2023). The costs in the UK fell in the following years, but this convergence is not relevant for the sake of our argument, because the data analyzed by the UK studies does not extend beyond 2015.

health of Australian women. It is also worth highlighting that Australia is a country that is tackling systemic problems with access to mental health services, and these problems are particularly dire among Australian men (see Productivity Commission, 2020). The lack of access to care (likely mixed with the lack of own initiative to use it) may worsen men's responses to stressors, creating a vicious cycle of increasing stress and chronic psychopathology (see Rnic et al., 2023). These problems would be particularly pronounced among men with pre-existing mental health issues.

Moving to the effects of WFH arrangements, our analyses have shown that working from home can prove beneficial for the mental health of Australian women, provided that the WFH component is large enough. The largest positive effects were associated with working 50-75% of work hours from home, which suggests that a partial workplace presence is likely beneficial for women's wellbeing. Also in this case, significant effects were only observed among respondents with low baseline levels of mental health. The results for men did not prove statistically significant, suggesting that WFH arrangements have relatively limited direct impact on men's mental health.

Crucially, the effects of WFH arrangements were estimated jointly with the effects of commuting time. This means that the positive effect of WFH arrangements on women's mental health is not a consequence of women spending less time in traffic. Rather, WFH arrangements have a positive effect *per se*, which increases their desirability as a tool for fostering healthy workplace practices. It is also worth noting that, even though men do not benefit from WFH arrangements directly, the move to WFH can still be beneficial to their mental health because of the associated reductions of commuting time. This indirect effect is, however, not as strong as the direct effect on women.[13]

The fact that the significant effects are concentrated among respondents with low baseline levels of mental health is a novel finding with important policy implications. It suggests that adjustments to work regimens have the potential to significantly improve the mental health outcomes of individuals at risk of mental illness, with the potential knock-on benefits of reduced absenteeism and improved productivity. And while we do not see significant effects

[13] Consider a man whose baseline level of mental health is associated with the largest negative effects of commuting (40-45th quantiles of the mental health distribution) and whose one-way commuting time is equal to the sample average of 38 minutes. If he were to start working fully from home, he would be predicted to improve his mental health by 0.04 SD. In contrast, a woman whose baseline level of mental health is associated with the largest positive effects of WFH (0-25th quantiles of the mental health distribution) would be predicted to improve her mental health by 0.2 SD if she were to switch to a 50-75% WFH arrangement.

among respondents with high baseline levels of mental health, it is certainly possible that these individuals benefit from WFH arrangements and reduced commuting times in other ways (for example, in terms of their subjective wellbeing).

Our results are particularly relevant for the discussions surrounding the future of work, and the post-pandemic organisation of firms. Indeed, many firms are currently wrestling with the issue of the extent to which WFH should be accommodated (and how to accommodate it). Our analysis indicates that allowing employees to retain (sufficiently flexible) WFH arrangements is likely to prove beneficial to those who are vulnerable, while having no detrimental effects on the mental health of other employees.

In terms of study limitations, we acknowledge that our analysis has been conducted on data that do not extend past year 2019. The key benefit of this restriction is that it allowed us to avoid the many confounders associated with the COVID-19 pandemic and isolate the causal effects of commuting time and WFH arrangements *per se*. However, it is possible that the pandemic experience has changed various aspects of work and commuting (e.g., by making firms more accommodating of the WFH arrangements, by reducing the commuting congestion, or by making people more mindful of their fellow commuters on public transport), and these changes could affect the magnitude of causal effects post-pandemic. Similarly, the share of respondents working from home prior to 2020 was smaller than the share of respondents who found themselves in these arrangements during the pandemic. One of the likely consequences of this shift is that the number of people engaging in WFH arrangements in the years to come is likely to grow and their characteristics are likely to change. Further research will be needed to ascertain whether this broader population is likely to be subject to the same effects as the ones presented in our study.

REFERENCES

ABS (2021). *Earnings and working conditions: Working arrangements.* Available at: https://www.abs.gov.au/statistics/labour/earnings-and-working-conditions/working-arrangements/latest-release [Accessed 14 October 2022].

Anderson, M.L., Lu, F., Zhang, Y., Yang, J. & Qin, P. (2016). Superstitions, street traffic, and subjective well-being. *Journal of Public Economics*, 142, 1-10.

Atkins, R., Turner, A.J., Chandola, T. & Sutton, M. (2020). Going beyond the mean in examining relationships of adolescent non-cognitive skills with health-related quality of life and biomarkers in later-life. *Economics and Human Biology*, 39, 100923.

Bailey, D.E. & Kurland, N.B. (2002). A review of telework research: Findings, new directions, and lessons for the study of modern work. *Journal of Organizational Behavior*, 23, 383-400.

Baker, E., Pham, N.T.A., Daniel, L. & Bentley, R. (2020). New evidence on mental health and housing affordability in cities: A quantile regression approach. *Cities*, 96, 102455.

Beland, L-P. & Brent, D.A. (2018). Traffic and crime. *Journal of Public Economics*, 160, 96-116.

Bloom, N., Liang, J., Roberts, J. & Ying, Z.J. (2015). Does working from home work? Evidence from a Chinese experiment. *The Quarterly Journal of Economics*, 130(1), 165-218.

Borah, B.J. & Basu, A. (2013). Highlighting differences between conditional and unconditional quantile regression approaches through an application to assess medication adherence. *Health Economics*, 22, 1052-1070.

Botha, F., de New, J.P., de New, S.C., Ribar, D.C. and Salamanca, N. (2021). Implications of COVID-19 labour market shocks for inequality in financial wellbeing. *Journal of Population Economics*, 34(2), 655-689.

Bubonya, M., Cobb-Clark, D.A. & Ribar, D.C. (2019). The reciprocal relationship between depressive symptoms and employment status. *Economics and Human Biology*, 35, 96-106.

Burd, C., Burrows, M. & McKenzie, B. (2021). Travel time to work in the United States: 2019, *American Community Survey Reports* [Accessed 31 October 2023].

Clark, B., Chatterjee, K., Martin, A. & Davis, A. (2020). How commuting affects subjective wellbeing. *Transportation,* 47, 2777-2805.

Cobb-Clark, D.A., Kassenboehmer, S.C. & Sinning, M.G. (2016). Locus of control and savings. *Journal of Banking and Finance*, 73, 113-130.

Elovanio, M., Hakulinen, C., Pulkki-Råback, L., Aalto, A-M., Virtanen, M., Partonen, T. & Suvisaari, J. (2020). General Health Questionnaire (GHQ-12), Beck Depression Inventory (BDI-6), and Mental Health Index (MHI-5): Psychometric and predictive properties in a Finnish population-based sample. *Psychiatry Research*, 289, 112973.

Firpo, S., Fortin, N.M. & Lemieux, T. (2009). Unconditional quantile regressions. *Econometrica*, 77, 953-973.

Flood, M. & Barbatto, C. (2005). *Off to Work. Commuting in Australia*. Discussion paper 78, The Australia Institute [Accessed 30 September 2022].

Gajendran, R. S., and Harrison, D.A. (2007). The good, the bad, and the unknown about telecommuting: Meta-analysis of psychological mediators and individual consequences. *Journal of Applied Psychology*, 92(6): 1524-41

Giménez-Nadal, J., Molina, J. & Velilla, J. (2022). Trends in commuting time of European workers: A cross-country analysis, *Transport Policy*, 116, 327-342.

Gottholmseder, G., Nowotny, K., Pruckner, G.J. & Theurl, E. (2009). Stress perception and commuting. *Health Economics*, 18, 559-576.

Hoeymans, N., Garssen, A.A., Westert, G.P. & Verhaak, P.F.M. (2004). Measuring mental health of the Dutch population: A comparison of the GHQ-12 and the MHI-5. *Health and Quality of Life Outcomes*, 2, 23.

Infrastructure Australia. (2019). *Urban transport crowding and congestion, The Australian Infrastructure Audit 2019* (Supplementary report). Available at: https://www.infrastructureaustralia.gov.au/publications/urban-transport-crowding-and-congestion [Accessed 3 February 2022].

Jacob, N., Munford, L., Rice, N. & Roberts, J. (2019). The disutility of commuting? The effect of gender and local labor markets. *Regional Science and Urban Economics*, 77, 264-275.

Jayawardana, D., Baryshnikova, N.V. & Cheng, T.C. (2023). The long shadow of child labour on adolescent mental health: A quantile approach. *Empirical Economics*, 64, 77-97.

Künn-Nelen, A. (2016). Does commuting affect health? *Health Economics*, 25, 984-1004.

Lyttelton, T., Zang, E. & Musick, K. (2020). Gender differences in telecommuting and implications for inequality at home and work. Available at: https://dx.doi.org/10.2139/ssrn.3645561 [Accessed 29 October 2023].

Mas, A. & Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12), 3722-3759.

Meekes, J. (2022). Agglomeration economies and the urban wage premium in Australia. *Australian Journal of Labour Economics*, 25(1), 25-54.

Milasi, S., I. González-Vázquez and E. Fernández-Macías (2021). Telework before the COVID-19 pandemic: Trends and drivers of differences across the EU. *OECD Productivity Working Papers*, 21, OECD Publishing, Paris. Available at: https://read.oecd.org/10.1787/d5e42dd1-en?format=pdf [Accessed 20 October 2023].

OECD (2023), Net childcare costs (indicator)**.** Available at: 10.1787/e328a9ee-en [Accessed 31 October 2023].

Ohrnberger, J., Fichera, E., Sutton, M. & Anselmi, L. (2020). The worse the better? Quantile treatment effects of a conditional cash transfer program on mental health. *Health Policy and Planning*, 35, 1137-1149.

Productivity Commission. (2020). *Mental Health*. Report No. 95. Canberra: Productivity Commission. Available at: https://www.pc.gov.au/inquiries/completed/mental-health/report [Accessed 19 September 2022].

Productivity Commission. (2021). *Working from home*, Research paper, Canberra: Productivity Commission. Available at: https://www.pc.gov.au/research/completed/working-from-home [Accessed 19 September 2022].

Rios-Avila, F. (2020). Recentered influence functions (RIFs) in Stata: RIF regression and RIF decomposition. *The Stata Journal*, 20(1), 51-94.

Rnic, K., Santee, A.C., Hoffmeister, J-A., Liu, H., Chang, K.K., Chen, R.X., Neufeld, R.W.J., Machado, D.A., Starr, L.R., Dozois, D.J.A. & LeMoult, J. (2023). The vicious cycle of psychopathology and stressful life events: A meta-analytic review testing the stress generation model. *Psychological Bulletin*, 149(5-6), 330-369.

Roberts, J., Hodgson, R. & Dolan, P. (2011). "It's driving her mad:" Gender differences in the effects of commuting on psychological health. *Journal of Health Economics*, 30, 1064-1076.

Schiele, V. & Schmitz, H. (2016). Quantile treatment effects of job loss on health. *Journal of Health Economics*, 49, 59-69.

Schrank, D., Eisele, B. & Lomax, T. (2019). *2019 Urban Mobility Report*. Available at: https://static.tti.tamu.edu/tti.tamu.edu/documents/umr/archive/mobility-report-2019.pdf [Accessed 4 February 2022].

Sinha, K., Davillas, A., Jones, A.M. & Sharma, A. (2021). Do socioeconomic health gradients persist over time and beyond income? A distributional analysis using UK biomarker data. *Economics and Human Biology*, 43, 101036.

Summerfield, M., Garrard, B., Hahn, M., Jin, Y., Kamath, R., Macalalad, N., Watson, N., Wilkins, R. & Wooden, M. (2020). *HILDA user manual – Release 19*, Melbourne Institute of Applied Economic and Social Research, The University of Melbourne. Available at: https://melbourneinstitute.unimelb.edu.au/__data/assets/pdf_file/0009/3562857/HILDA-User-Manual-Release-19.0.pdf [Accessed 12 February 2022].

TTPN (2020). Melbourne Institute's Survey of the Impact of COVID-19 in Australia, Wave 19. Available at: https://melbourneinstitute.unimelb.edu.au/__data/assets/pdf_file/0003/3504612/Taking-the-Pulse-of-the-Nation-14-18-September.pdf [Accessed 14 October 2022].

Ware, J. E., Snow, K. K., Kosinski M., & Gandek B. (2000). SF-36 Health Survey: Manual and Interpretation Guide. Lincoln (RI): QualityMetric Inc. Available at: https://www.researchgate.net/publication/247503121_SF36_Health_Survey_Manual_and_Interpretation_Guide [Accessed 14 February 2022].

Wilkins R., Vera-Toscano, E., Botha, F., Wooden, M. & Trinh, T. (2022). The Household, Income and Labour Dynamics in Australia Survey: Selected Findings from Waves 1 to 20. Melbourne Institute: Applied Economic & Social Research, The University of Melbourne. Available at: https://melbourneinstitute.unimelb.edu.au/__data/assets/pdf_file/0011/4382057/HILDA_Statistical_Report_2022.pdf [Accessed 30 June 2022].

Xiao, Y., Becerik-Gerber, B., Lucas, G. & Roll, S.C. (2021). Impacts of working from home during COVID-19 pandemic on physical and mental well-being of office workstation users. *Journal of Occupational and Environmental Medicine*, 63(3), 181-190.

Zorn, J.V., Schür, R.R., Boks, M.P., Kahn, R.S., Joëls, M. & Vinkers, C.H. (2017). Cortisol stress reactivity across psychiatric disorders. A systematic review and meta-analysis. *Psychoneuroendocrinology*, 77, 25-36.

APPENDIX

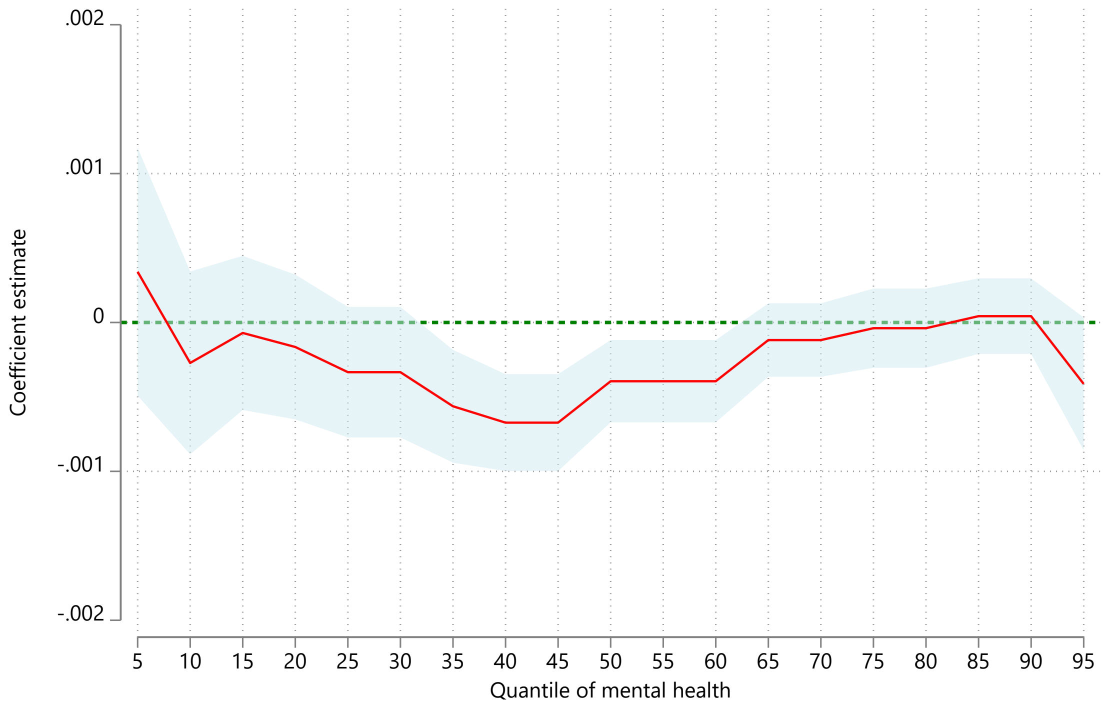
APPENDIX A1. UNCONDITIONAL QUANTILE REGRESSION RESULTS ANALYSIS OF THE UK SAMPLE

To bolster the external validity of our findings, we have applied our UQR model to the UK data analysed in previous studies of the relationship between commuting time and mental health. Specifically, we use the UKHLS dataset spanning the years 2009 to 2016 (see Jacob et al. 2019). Before we present the results, it is worth reiterating that the UK findings differ from ours in that the significant negative effects of commuting time on mental health in the UK are found only among women (see Table 1).

Our UQR results are presented graphically in Appendix Figure A3. In line with the previous UK studies, we see that commuting time affects mental health of British women. Also in this context, we see that the significant negative effects are concentrated among women with low baseline levels of mental health (below the 30th quantile of the mental health distribution). For men, we also see suggestive evidence of a negative effect at the low end of the mental health distribution (below the 20th quantile), however the coefficients fail to yield statistical significance.

These findings suggest that the results of British studies are driven by a relatively small subset of women with very low baseline levels of mental health, for whom the changes of their commuting time can wield fairly substantive influence over their mental wellbeing. For women below the 30th quantile of the mental health distribution, a 30-minute increase of their commuting time is predicted to lower their mental health score by 0.08 SD.

FIGURE A1: UNCONDITIONAL QUANTILE REGRESSION RESULTS – COMMUTING TIME, POOLED AUSTRALIAN SAMPLE

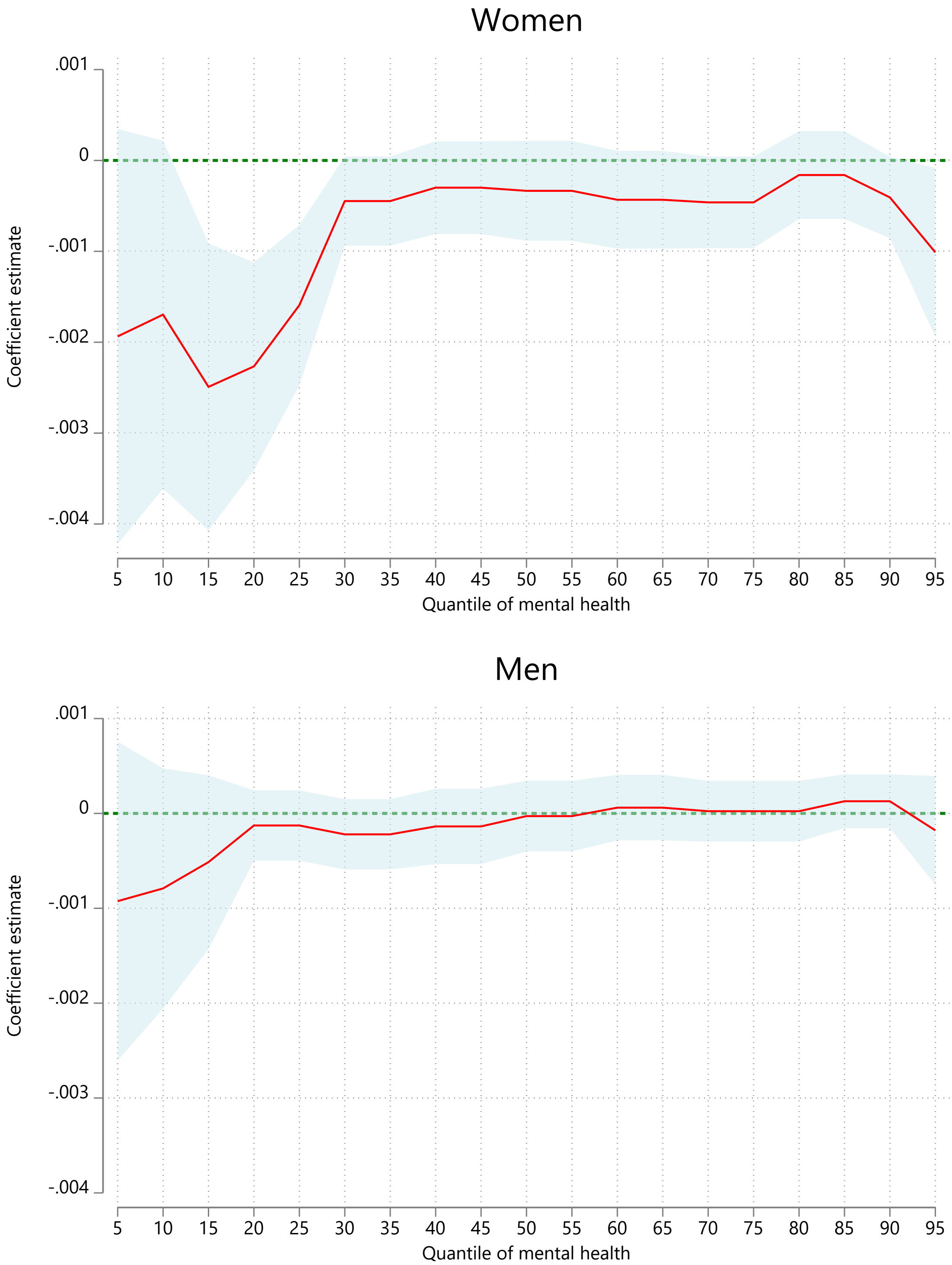


Notes: The figure presents the estimated effects of one-minute increase in one-way daily commuting time at distinct quantiles of the mental health distribution. The dependent variable is our standardised MHI-5 measure of mental health. Shaded region represents the 90% confidence intervals. Data from HILDA Survey, 2002-2019.

FIGURE A2: UNCONDITIONAL QUANTILE REGRESSION RESULTS – WFH INTENSITY, POOLED AUSTRALIAN SAMPLE

Notes: The figure presents the estimated coefficient for shares of total weekly working hours that are worked from home at distinct quantiles of the mental health distribution, relative to individuals who work none of their working hours from home. The dependent variable is our standardised MHI-5 measure of mental health. Shaded region represents the 90% confidence intervals. Data from HILDA Survey, 2002-2019.

FIGURE A3: UNCONDITIONAL QUANTILE REGRESSION RESULTS FOR THE UK SAMPLE



Notes: The figure presents the estimated coefficient for one-way daily commuting time (in minutes) at distinct quantiles of the mental health distribution. The dependent variable is a standardised GHQ measure of mental health. Shaded region represents the 90% confidence intervals. Data source is UKHLS, 2009-2016.

TABLE A1: VARIABLE DEFINITIONS

Variable	Definition
Mental health	Mental Health subscale of the SF-36 measure, ranging from 0 (low) to 100 (high).
Commuting time	One-way daily commuting time in minutes, derived from the question: “How much time do you spend [travelling to and from a place of paid employment] in a typical week?” To make our outcome variable more comparable with existing research, we use additional information on the reported number of working days per week to convert the weekly commuting time totals to a one-way daily commuting time in minutes.
Share of hours WFH	A respondent’s reported weekly hours worked from home as a share of total reported weekly working hours.
Male	Equals 1 if a respondent is male, 0 otherwise.
Age	Respondent’s age in brackets, 18-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64.
Self-rated health	Responses to the question “In general, would you say your health is ‘excellent’, ‘very good’, ‘good’, ‘fair’, ‘poor’.” Measured on 5-point Likert scale ranging from 1 (poor) to 5 (excellent).
Marital status	Respondent’s marital status. (i) Married, (ii) De facto relationship, (iii) Separated, (iv) Divorced, (v) Widowed, (vi) Never married and not de facto.
Log household income	Log of annual equivalised real disposable household income, in December 2019 prices.
Wage rate	Real weekly wage rate in December 2019 prices, calculated as weekly wages as a proportion of weekly working hours.
Education	Respondent’s highest level of education achieved. (i) Year 11 and below, (ii) Year 12, (iii) Certificate III or IV, or Advanced Diploma, (vi) Bachelor degree or higher.
Children	Indicators for whether an individual has at least one child aged 4 years or younger, 5-9, or 10-14.
Working hours	Total weekly working hours in main job.
Neighbourhood satisfaction	Response to the question “All things considered, how satisfied are you with your neighbourhood?” Measured on an 11-point Likert scale ranging from 0 (very dissatisfied) to 10 (very satisfied).
Job satisfaction	Response to the question “All things considered, how satisfied are you with your job?” Measured on an 11-point Likert scale ranging from 0 (very dissatisfied) to 10 (very satisfied).

TABLE A2: FULL HOME-JOB-SPELL FIXED EFFECTS REGRESSION RESULTS

	(1) All	(3) Female	(4) Male
Commuting time	-0.0002	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)
Share of hours WFH			
0% < Share < 25%	-0.0072	-0.0145	0.0005
	(0.0095)	(0.0136)	(0.0132)
25% ≤ Share < 50%	0.0004	-0.0028	0.0042
	(0.0170)	(0.0218)	(0.0272)
50% ≤ Share < 75%	0.0458	0.0805**	-0.0091
	(0.0303)	(0.0405)	(0.0435)
Share ≥ 75%	0.0397	0.0396	0.0433
	(0.0350)	(0.0458)	(0.0527)
Working hours	0.0003	0.0003	0.0001
	(0.0005)	(0.0006)	(0.0007)
Job satisfaction	0.0691***	0.0687***	0.0695***
	(0.0027)	(0.0038)	(0.0037)
Age: 25-29	-0.0597***	-0.0467	-0.0736**
	(0.0220)	(0.0318)	(0.0304)
Age: 30-34	-0.0602**	-0.0328	-0.0871**
	(0.0289)	(0.0424)	(0.0395)
Age: 35-39	-0.0840**	-0.0538	-0.1141**
	(0.0351)	(0.0514)	(0.0481)
Age: 40-44	-0.0991**	-0.0651	-0.1342**
	(0.0404)	(0.0595)	(0.0545)
Age: 45-49	-0.0951**	-0.0745	-0.1156*
	(0.0455)	(0.0663)	(0.0623)
Age: 50-54	-0.0954*	-0.0718	-0.1212*
	(0.0512)	(0.0745)	(0.0702)
Age: 55-59	-0.0561	-0.0275	-0.0874
	(0.0575)	(0.0836)	(0.0789)
Age: 60-64	0.0082	0.0609	-0.0497
	(0.0638)	(0.0927)	(0.0875)
Self-assessed health	0.2205***	0.2320***	0.2084***
	(0.0056)	(0.0078)	(0.0080)
De facto relationship	0.0052	0.0003	0.0086
	(0.0186)	(0.0254)	(0.0274)
Separated	-0.3030***	-0.2891***	-0.3206***
	(0.0409)	(0.0536)	(0.0632)
Divorced	-0.0929**	-0.0891*	-0.1013*
	(0.0404)	(0.0533)	(0.0611)
Widowed	-0.2408**	-0.3110**	-0.0174
	(0.1018)	(0.1259)	(0.1133)
Never married and not de facto	-0.0552*	0.0053	-0.1077**
	(0.0313)	(0.0451)	(0.0442)
Log household income	0.0150**	0.0131	0.0182*
	(0.0075)	(0.0110)	(0.0100)
Wage rate	0.0002	-0.0000	0.0004
	(0.0003)	(0.0004)	(0.0005)
Education: Grad diploma, grad certificate	-0.0555	-0.0520	-0.0726
	(0.0477)	(0.0595)	(0.0772)
Education: Bachelor or honours	0.0187	0.0119	0.0141

	(0.0395)	(0.0503)	(0.0631)
Education: Adv diploma, diploma	-0.0457	-0.0435	-0.0715
	(0.0584)	(0.0770)	(0.0902)
Education: Cert III or IV	-0.0344	-0.0126	-0.0866
	(0.0584)	(0.0717)	(0.0834)
Education: Year 12	0.0110	0.0384	-0.0433
	(0.0498)	(0.0641)	(0.0791)
Education: Year 11 and below	-0.0926	-0.1045	-0.0978
	(0.0602)	(0.0813)	(0.0899)
Children aged 0 – 4	0.0153	0.0051	0.0217
	(0.0125)	(0.0189)	(0.0169)
Children aged 5 – 9	-0.0140	-0.0163	-0.0151
	(0.0113)	(0.0169)	(0.0152)
Children aged 10 – 14	-0.0010	-0.0178	-0.0051
	(0.0110)	(0.0162)	(0.0148)
Satisfaction with neighbourhood	0.0323***	0.0334***	0.0313***
	(0.0029)	(0.0041)	(0.0041)
Constant	-1.6220***	-1.7824***	-1.4407***
	(0.1048)	(0.1482)	(0.1494)
Observations	113,467	57,963	55,504
R^2	0.0622	0.0640	0.0619
Number of home-job spells	47,076	24,000	23,076

*Note: Robust standard errors, clustered at the home-job-spell level, are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All models also include year and region dummies.*

TABLE A3: FULL FIXED EFFECTS REGRESSION RESULTS WITH ROBERTS ET AL. (2011) AND JACOB ET AL. (2019) SAMPLE RESTRICTIONS

	(4)	**(6)**	**(7)**	**(8)**	**(10)**	**(11)**
	All; Roberts et al. sample restrictions non-zero commute change	Female; Roberts et al. sample restrictions non-zero commute change	Male; Roberts et al. sample restrictions non-zero commute change	All; Jacob et al. sample restrictions change of at least 0.833 hour	Female; Jacob et al. sample restrictions change of at least 0.833 hour	Male; Jacob et al. sample restrictions change of at least 0.833 hour
Commuting time	-0.0001	-0.0002	-0.0001	-0.0002	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Share of hours WFH						
0% < Share < 25%	-0.0160	-0.0142	-0.0156	-0.0146	-0.0195	-0.0060
	(0.0099)	(0.0141)	(0.0138)	(0.0118)	(0.0167)	(0.0167)
25% ≤ Share < 50%	-0.0244	-0.0385*	0.0029	-0.0274	-0.0432	0.0013
	(0.0177)	(0.0228)	(0.0281)	(0.0210)	(0.0272)	(0.0327)
50% ≤ Share < 75%	0.0172	0.0320	-0.0077	0.0478	0.0621	0.0182
	(0.0318)	(0.0445)	(0.0425)	(0.0389)	(0.0534)	(0.0520)
Share ≥ 75%	-0.0013	-0.0156	0.0327	0.0067	-0.0169	0.0449
	(0.0328)	(0.0412)	(0.0531)	(0.0406)	(0.0506)	(0.0665)
Working hours	0.0004	0.0006	0.0001	0.0002	0.0005	0.0001
	(0.0004)	(0.0006)	(0.0007)	(0.0005)	(0.0007)	(0.0008)
Job satisfaction	0.0709***	0.0688***	0.0740***	0.0679***	0.0678***	0.0686***
	(0.0027)	(0.0038)	(0.0037)	(0.0031)	(0.0043)	(0.0044)
Age: 25-29	-0.0550***	-0.0420	-0.0647**	-0.0543**	-0.0328	-0.0759**
	(0.0206)	(0.0297)	(0.0286)	(0.0240)	(0.0345)	(0.0336)
Age: 30-34	-0.0780***	-0.0681*	-0.0875**	-0.0793**	-0.0697	-0.0937**
	(0.0273)	(0.0393)	(0.0377)	(0.0321)	(0.0457)	(0.0449)
Age: 35-39	-0.0876**	-0.0808	-0.0939**	-0.0851**	-0.0669	-0.1077*
	(0.0342)	(0.0496)	(0.0470)	(0.0405)	(0.0579)	(0.0565)
Age: 40-44	-0.1028**	-0.1127*	-0.0955*	-0.1150**	-0.1160*	-0.1209*
	(0.0407)	(0.0593)	(0.0557)	(0.0484)	(0.0694)	(0.0672)
Age: 45-49	-0.0856*	-0.1144*	-0.0600	-0.0862	-0.1081	-0.0727
	(0.0468)	(0.0676)	(0.0645)	(0.0560)	(0.0796)	(0.0785)
Age: 50-54	-0.0683	-0.1093	-0.0324	-0.0832	-0.1206	-0.0543
	(0.0536)	(0.0777)	(0.0738)	(0.0648)	(0.0928)	(0.0902)
Age: 55-59	-0.0252	-0.0899	0.0359	-0.0376	-0.0832	-0.0003
	(0.0609)	(0.0882)	(0.0837)	(0.0736)	(0.1053)	(0.1025)

Age: 60-64	0.0538	-0.0052	0.1070	0.00183	-0.0160	0.0410
	(0.0679)	(0.0980)	(0.0935)	(0.0824)	(0.1178)	(0.1149)
Self-assessed health	0.2426***	0.2507***	0.2334***	0.2428***	0.2509***	0.2334***
	(0.0061)	(0.0083)	(0.0089)	(0.0070)	(0.0096)	(0.0104)
De facto relationship	-0.0025	-0.0164	0.0057	0.0028	-0.0129	0.0057
	(0.0169)	(0.0234)	(0.0244)	(0.0198)	(0.0274)	(0.0289)
Separated	-0.2173***	-0.2051***	-0.2330***	-0.2305***	-0.2298***	-0.2337***
	(0.0327)	(0.0445)	(0.0482)	(0.0360)	(0.0490)	(0.0532)
Divorced	0.0109	0.0489	-0.0345	-0.0016	0.0213	-0.0296
	(0.0305)	(0.0394)	(0.0480)	(0.0333)	(0.0438)	(0.0514)
Widowed	-0.1889*	-0.2156*	-0.0904	-0.1961*	-0.2499**	-0.0182
	(0.0967)	(0.1168)	(0.1380)	(0.1042)	(0.1266)	(0.1124)
Never married and not de facto	-0.0864***	-0.0384	-0.1344***	-0.0609*	0.0082	-0.1345**
	(0.0230)	(0.0321)	(0.0329)	(0.0272)	(0.0369)	(0.0396)
Log household income	0.0149*	0.0181	0.0129	0.0118	0.0113	0.0166
	(0.0084)	(0.0121)	(0.0112)	(0.0088)	(0.0114)	(0.0136)
Wage rate	-0.0000	-0.0004	0.0004	-0.0002	-0.0001	-0.0002
	(0.0003)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Education: Grad diploma, grad certificate	-0.0084	-0.0100	-0.0311	0.0180	0.0049	-0.0079
	(0.0418)	(0.0555)	(0.0617)	(0.0489)	(0.0646)	(0.0747)
Education: Bachelor or honours	0.0195	0.0463	-0.0333	0.0492	0.0541	0.0199
	(0.0350)	(0.0480)	(0.0502)	(0.0412)	(0.0559)	(0.0604)
Education: Adv diploma, diploma	0.0240	0.0590	-0.0409	0.0621	0.0688	0.0245
	(0.0503)	(0.0694)	(0.0722)	(0.0607)	(0.0829)	(0.0885)
Education: Cert III or IV	-0.0109	0.0221	-0.0818	0.0119	0.0219	-0.0293
	(0.0458)	(0.0632)	(0.0652)	(0.0542)	(0.0743)	(0.0786)
Education: Year 12	0.0138	0.0582	-0.0683	0.0363	0.0645	-0.0301
	(0.0418)	(0.0567)	(0.0614)	(0.0492)	(0.0659)	(0.0744)
Education: Year 11 and below	-0.0559	-0.0470	-0.0864	-0.0464	-0.0535	-0.0487
	(0.0516)	(0.0715)	(0.0721)	(0.0592)	(0.0818)	(0.0839)
Children aged 0 – 4	0.0098	0.0095	0.0078	0.0088	0.0206	-0.0036
	(0.0116)	(0.0180)	(0.0156)	(0.0136)	(0.0208)	(0.0184)
Children aged 5 – 9	-0.0293***	-0.0258*	-0.0379***	-0.0275**	-0.0241	-0.0365**

	(0.0106)	(0.0155)	(0.0144)	(0.0122)	(0.0180)	(0.0170)
Children aged 10 – 14	-0.0180*	-0.0306*	-0.0068	-0.0186	-0.0293	-0.0092
	(0.0105)	(0.0159)	(0.0137)	(0.0123)	(0.0186)	(0.0161)
Satisfaction with neighbourhood	0.0304***	0.0215***	0.0314***	0.0297***	0.0283***	0.0311***
	(0.0029)	(0.0040)	(0.0041)	(0.0033)	(0.0045)	(0.0448)
Constant	-1.7263***	-1.6554***	-1.7312***	-1.6134***	-1.5541***	-1.6794***
	(0.1388)	(0.1941)	(0.1950)	(0.1557)	(0.2094)	(0.2321)
Observations	77,482	39,667	37,815	59,377	30,658	28,719
R-squared	0.0738	0.0746	0.0791	0.0717	0.0750	0.0752
Number of individuals	14,608	7,505	7,103	14,110	7,261	6,849

*Note: Robust standard errors, clustered at the individual level, in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All models also include year and region dummies.*

TABLE A4: QUADRATIC COMMUTING TIME

	(1) overall	(2) female	(3) male
Commuting time	-0.0001	-0.0001	-0.0002
	(0.0004)	(0.0006)	(0.0006)
Commuting time squared	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)
Share of hours WFH			
0% < Share < 25%	-0.0072	-0.0144	0.0005
	(0.0095)	(0.0136)	(0.0132)
25% ≤ Share < 50%	0.0005	-0.0027	0.0042
	(0.0170)	(0.0218)	(0.0272)
50% ≤ Share < 75%	0.0459	0.0809**	-0.0091
	(0.0303)	(0.0405)	(0.0435)
Share ≥ 75%	0.0402	0.0405	0.0434
	(0.0350)	(0.0460)	(0.0527)
Observations	113,467	57,963	55,504
R-squared	0.0622	0.0640	0.0619
Number of home-job-spells	47,076	24,000	23,076

*Note: Robust standard errors, clustered at the home-job-spell level, are in parentheses. ** $p < 0.05$. All models include a constant and control for age, self-rated health, marital status, log of equivalised housing income, weekly wage rate, education, presence of children, working hours, neighbourhood satisfaction, job satisfaction, and year and region dummies.*

TABLE A5: EXCLUDE PEOPLE WORKING FROM HOME

	(1) overall	(2) female	(3) male
Commuting time	-0.0001	-0.0002	0.0001
	(0.0002)	(0.0003)	(0.0003)
Observations	92,744	47,192	45,552
R-squared	0.0583	0.0613	0.0568
Number of home-job-spells	41,820	21,361	20,459

Note: Robust standard errors, clustered at the home-job-spell level, are in parentheses. All models include a constant and control for age, self-rated health, marital status, log of equivalised housing income, weekly wage rate, education, presence of children, working hours, neighbourhood satisfaction, job satisfaction, and year and region dummies.

TABLE A6: UNCONDITIONAL QUANTILE REGRESSION RESULTS: OVERALL SAMPLE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	P10	P20	P30	P40	P50	P60	P70	P80	P90
Commuting time	-0.0003	-0.0002	-0.0003	-0.0007***	-0.0004**	-0.0004**	-0.0001	-0.0000	0.0000
	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Share of hours WFH									
0% < Share < 25%	-0.0134	0.0033	-0.0128	-0.0205	0.0040	0.0040	-0.0032	-0.0079	-0.0054
	(0.0243)	(0.0193)	(0.0173)	(0.0129)	(0.0109)	(0.0109)	(0.0098)	(0.0105)	(0.0100)
25% ≤ Share < 50%	0.0107	0.0009	0.0163	-0.0143	0.0113	0.0113	-0.0033	-0.0179	-0.0021
	(0.0444)	(0.0352)	(0.0317)	(0.0235)	(0.0200)	(0.0200)	(0.0179)	(0.0193)	(0.0184)
50% ≤ Share < 75%	0.1290	0.1418**	0.0770	0.0765*	0.0426	0.0426	-0.0169	-0.0299	-0.0145
	(0.0787)	(0.0624)	(0.0562)	(0.0417)	(0.0354)	(0.0354)	(0.0316)	(0.0341)	(0.0325)
Share ≥ 75%	0.0219	0.0886	0.0680	0.0452	0.0786	0.0786**	0.0428	0.0491	0.0136
	(0.0879)	(0.0696)	(0.0627)	(0.0466)	(0.0395)	(0.0395)	(0.0353)	(0.0381)	(0.0363)
Age: 25-29	-0.1157**	-0.0895**	-0.0655*	-0.0573**	-0.0635***	-0.0635***	-0.0412**	-0.0442**	-0.0078
	(0.0502)	(0.0398)	(0.0358)	(0.0266)	(0.0226)	(0.0226)	(0.0202)	(0.0217)	(0.0208)
Age: 30-34	-0.1069	-0.0781	-0.0275	-0.0471	-0.0861***	-0.0861***	-0.0796***	-0.0878***	-0.0295
	(0.0683)	(0.0541)	(0.0488)	(0.0362)	(0.0307)	(0.0307)	(0.0274)	(0.0296)	(0.0282)
Age: 35-39	-0.0504	-0.0731	-0.0438	-0.1038**	-0.1283***	-0.1283***	-0.1334***	-0.1277***	-0.0892***
	(0.0837)	(0.0663)	(0.0597)	(0.0444)	(0.0377)	(0.0378)	(0.0336)	(0.0362)	(0.0345)
Age: 40-44	-0.0622	-0.0535	-0.0225	-0.1241**	-0.1617***	-0.1617***	-0.1669***	-0.1599***	-0.1263***
	(0.0979)	(0.0775)	(0.0698)	(0.0519)	(0.0440)	(0.0440)	(0.0393)	(0.0424)	(0.0405)
Age: 45-49	-0.0042	-0.0242	-0.0470	-0.1317**	-0.1638***	-0.1638***	-0.1769***	-0.1671***	-0.1317***
	(0.1123)	(0.0889)	(0.0801)	(0.0595)	(0.0505)	(0.0505)	(0.0451)	(0.0486)	(0.0464)
Age: 50-54	0.0135	0.0102	-0.0343	-0.1312*	-0.1708***	-0.1708***	-0.1779***	-0.1722***	-0.1431***
	(0.1280)	(0.1014)	(0.0914)	(0.0678)	(0.0576)	(0.0576)	(0.0514)	(0.0554)	(0.0529)
Age: 55-59	0.0488	0.0808	0.0411	-0.1155	-0.1575**	-0.1575**	-0.1654***	-0.1367**	-0.1255**
	(0.1452)	(0.1150)	(0.1036)	(0.0769)	(0.0653)	(0.0653)	(0.0584)	(0.0628)	(0.0600)
Age: 60-64	0.1072	0.1598	0.1132	-0.0588	-0.1132	-0.1132	-0.1336**	-0.1028	-0.0723
	(0.1635)	(0.1295)	(0.1167)	(0.0867)	(0.0736)	(0.0735)	(0.0657)	(0.0709)	(0.0676)

Self-assessed health	0.2972***	0.2809***	0.2642***	0.1983***	0.1682***	0.1682***	0.1376***	0.1261***	0.0959***
	(0.0116)	(0.0092)	(0.0083)	(0.0062)	(0.0052)	(0.0052)	(0.0047)	(0.0050)	(0.0048)
De facto relationship	0.0171	-0.0022	0.0039	-0.0115	-0.0267	-0.0267	-0.0196	-0.0007	-0.0091
	(0.0426)	(0.0337)	(0.0304)	(0.0226)	(0.0192)	(0.0192)	(0.0171)	(0.0185)	(0.0176)
Separated	-0.5038***	-0.3937***	-0.3653***	-0.2568***	-0.1710***	-0.1710***	-0.1175***	-0.1259***	-0.1290***
	(0.0724)	(0.0574)	(0.0517)	(0.0384)	(0.0326)	(0.0326)	(0.0291)	(0.0314)	(0.0299)
Divorced	-0.1526*	-0.2031***	-0.2145***	-0.0946**	-0.0392	-0.0392	-0.0216	-0.0133	0.0172
	(0.0787)	(0.0623)	(0.0561)	(0.0417)	(0.0354)	(0.0354)	(0.0316)	(0.0340)	(0.0325)
Widowed	-0.1937	-0.2865**	-0.3165***	-0.2737***	-0.2055***	-0.2055***	-0.0898	-0.1114*	-0.0952
	(0.1481)	(0.1173)	(0.1057)	(0.0785)	(0.0666)	(0.0666)	(0.0595)	(0.0642)	(0.0612)
Never married and not de facto	-0.0464	-0.0844	-0.0467	-0.0834**	-0.0841***	-0.0841***	-0.0727***	-0.0616**	-0.0063
	(0.0687)	(0.0544)	(0.0489)	(0.0364)	(0.0308)	(0.0309)	(0.0276)	(0.0297)	(0.0284)
Log household income	0.0221	0.0141	0.0209*	0.0138	0.0020	0.0020	0.0056	0.0192***	0.0102
	(0.0167)	(0.0132)	(0.0119)	(0.0088)	(0.0075)	(0.0075)	(0.0067)	(0.0072)	(0.0069)
Wage rate	0.0009	0.0005	0.0006	-0.0002	-0.0003	-0.0003	-0.0003	-0.0001	-0.0004
	(0.0008)	(0.0006)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Education: Grad diploma, grad certificate	-0.1895	0.0228	-0.0920	-0.0865	-0.0872	-0.0872	-0.0494	-0.0259	0.0745
	(0.1204)	(0.0954)	(0.0859)	(0.0638)	(0.0542)	(0.0542)	(0.0484)	(0.0522)	(0.0498)
Education: Bachelor or honours	-0.0260	0.0534	0.0134	0.0069	-0.0277	-0.0277	-0.0486	0.0456	0.0747*
	(0.1074)	(0.0851)	(0.0766)	(0.0569)	(0.0483)	(0.0483)	(0.0432)	(0.0465)	(0.0444)
Education: Adv diploma, diploma	-0.1856	0.0386	-0.0873	-0.1125	-0.1004	-0.1004	-0.0671	-0.0199	0.0097
	(0.1398)	(0.1107)	(0.0998)	(0.0741)	(0.0629)	(0.0629)	(0.0562)	(0.0606)	(0.0578)
Education: Cert III or IV	-0.2696**	0.0294	-0.0622	-0.0134	-0.0692	-0.0692	-0.0609	0.0015	-0.0180
	(0.1328)	(0.1052)	(0.0948)	(0.0704)	(0.0598)	(0.0598)	(0.0534)	(0.0575)	(0.0549)
Education: Year 12	-0.1925	0.1507	0.0328	-0.0322	-0.0545	-0.0545	-0.0375	0.0044	0.0135
	(0.1255)	(0.0994)	(0.0896)	(0.0665)	(0.0565)	(0.0564)	(0.0504)	(0.0544)	(0.0519)
Education: Year 11 and below	-0.2910**	-0.0379	-0.1682	-0.0776	-0.1178*	-0.1178*	-0.0796	-0.0452	-0.0175
	(0.1445)	(0.1144)	(0.1031)	(0.0766)	(0.0650)	(0.0650)	(0.0581)	(0.0626)	(0.0597)

Children aged 0 – 4	0.0433	0.0714***	0.0555***	0.0053	-0.0004	-0.0004	-0.0071	0.0039	-0.0031
	(0.0298)	(0.0236)	(0.0213)	(0.0158)	(0.0134)	(0.0134)	(0.0120)	(0.0129)	(0.0123)
Children aged 5 – 9	-0.0044	0.0011	-0.0058	-0.0188	-0.0035	-0.0035	-0.0120	-0.0248**	-0.0153
	(0.0263)	(0.0209)	(0.0188)	(0.0139)	(0.0119)	(0.0119)	(0.0106)	(0.0114)	(0.0109)
Children aged 10 – 14	0.0338	0.0056	-0.0004	-0.0212	-0.0142	-0.0142	-0.0135	-0.0086	-0.0059
	(0.0251)	(0.0199)	(0.0179)	(0.0133)	(0.0113)	(0.0113)	(0.0101)	(0.0109)	(0.0104)
Working hours	0.0019*	0.0018**	0.0014*	-0.0003	-0.0008*	-0.0008*	-0.0009**	-0.0010**	-0.0007
	(0.0010)	(0.0008)	(0.0007)	(0.0006)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
Satisfaction with neighbourhood	0.0487***	0.0490***	0.0405***	0.0270***	0.0223***	0.0223***	0.0170***	0.0185***	0.0095***
	(0.0063)	(0.0050)	(0.0045)	(0.0034)	(0.0028)	(0.0028)	(0.0025)	(0.0027)	(0.0026)
Job satisfaction	0.0963***	0.0927***	0.0833***	0.0632***	0.0501***	0.0501***	0.0394***	0.0379***	0.0299***
	(0.0055)	(0.0043)	(0.0039)	(0.0029)	(0.0025)	(0.0025)	(0.0022)	(0.0024)	(0.0023)
Constant	-3.5136***	-2.8728***	-2.2575***	-1.2270***	-0.5734***	-0.3793***	0.0012	0.0210	0.5122***
	(0.2392)	(0.1894)	(0.1707)	(0.1267)	(0.1076)	(0.1076)	(0.0961)	(0.1036)	(0.0988)
Observations	88,833	88,833	88,833	88,833	88,833	88,833	88,833	88,833	88,833
Within R-sq	0.0192	0.0273	0.0283	0.0289	0.0269	0.0269	0.0219	0.0174	0.0114

*Note: Robust standard errors, clustered at the home-job-spell level, are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All models also include year and region dummies.*

TABLE A7: UNCONDITIONAL QUANTILE REGRESSION RESULTS: FEMALE SAMPLE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	P10	P20	P30	P40	P50	P60	P70	P80	P90
Commuting time	-0.0005	0.0001	-0.0001	-0.0004	-0.0005*	-0.0002	-0.0001	-0.0003	-0.0003
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Share of hours WFH									
0% < Share < 25%	-0.0229	0.0043	-0.0300	-0.0392*	-0.0264	0.0026	-0.0027	-0.0093	-0.0125
	(0.0358)	(0.0304)	(0.0257)	(0.0224)	(0.0194)	(0.0166)	(0.0151)	(0.0165)	(0.0166)
25% ≤ Share < 50%	0.0157	0.0242	-0.0078	0.0109	-0.0257	-0.0095	-0.0026	-0.0137	0.0050
	(0.0584)	(0.0496)	(0.0420)	(0.0366)	(0.0317)	(0.0271)	(0.0247)	(0.0269)	(0.0271)
50% ≤ Share < 75%	0.2042**	0.1606*	0.0941	0.0915	0.0809	0.0523	0.0278	0.0076	0.0052
	(0.1042)	(0.0885)	(0.0749)	(0.0652)	(0.0565)	(0.0484)	(0.0440)	(0.0479)	(0.0483)
Share ≥ 75%	0.0471	0.1070	0.0103	-0.0251	0.0671	0.0783	0.0247	0.0206	0.0119
	(0.1135)	(0.0964)	(0.0816)	(0.0711)	(0.0615)	(0.0527)	(0.0480)	(0.0522)	(0.0526)
Age: 25-29	-0.0583	-0.0285	-0.0812	-0.0749	-0.0683*	-0.0695**	-0.0202	-0.0185	0.0012
	(0.0747)	(0.0633)	(0.0537)	(0.0467)	(0.0405)	(0.0347)	(0.0315)	(0.0344)	(0.0346)
Age: 30-34	-0.0457	0.0545	-0.0422	-0.0646	-0.0471	-0.0982**	-0.0567	-0.0622	0.0120
	(0.1018)	(0.0863)	(0.0732)	(0.0634)	(0.0552)	(0.0472)	(0.0430)	(0.0469)	(0.0472)
Age: 35-39	0.0369	0.0515	-0.0579	-0.0928	-0.1105	-0.1405**	-0.1160**	-0.0829	-0.0380
	(0.1242)	(0.1054)	(0.0893)	(0.0778)	(0.0674)	(0.0577)	(0.0525)	(0.0572)	(0.0576)
Age: 40-44	0.0494	0.0960	-0.0227	-0.1279	-0.11391*	-0.1790***	-0.1424**	-0.0935	-0.0559
	(0.1447)	(0.1227)	(0.1040)	(0.0905)	(0.0784)	(0.0671)	(0.0611)	(0.0666)	(0.0660)
Age: 45-49	0.1242	0.1573	-0.0659	-0.2080**	-0.1831**	-0.2077***	-0.1677**	-0.0987	-0.0620
	(0.1653)	(0.1402)	(0.1188)	(0.1035)	(0.0896)	(0.0767)	(0.0698)	(0.0761)	(0.0766)
Age: 50-54	0.2026	0.1864	-0.0446	-0.1989*	-0.1835*	-0.2134**	-0.1679**	-0.1088	-0.0745
	(0.1882)	(0.1597)	(0.1352)	(0.1178)	(0.1019)	(0.0874)	(0.0795)	(0.0866)	(0.0872)
Age: 55-59	0.2875	0.3218*	0.0311	-0.1882	-0.1740	-0.2060**	-0.1607*	-0.0584	-0.0495
	(0.2132)	(0.1809)	(0.1532)	(0.1335)	(0.1155)	(0.0989)	(0.0901)	(0.0981)	(0.0988)
Age: 60-64	0.3939	0.4337**	0.1248	-0.1061	-0.0929	-0.1517	-0.1017	0.0091	0.0346
	(0.2401)	(0.2038)	(0.1725)	(0.1503)	(0.1301)	(0.1114)	(0.1014)	(0.1105)	(0.1113)
Self-assessed health	0.3250***	0.3133***	0.2978***	0.2713***	0.2214***	0.1909***	0.1512***	0.1404***	0.1012***

	(0.0170)	(0.0144)	(0.0122)	(0.0106)	(0.0092)	(0.0079)	(0.0072)	(0.0078)	(0.0079)
De facto relationship	0.0044	0.0299	-0.0048	0.0310	-0.0010	-0.0376	-0.0393	-0.0220	-0.0176
	(0.0615)	(0.0522)	(0.0442)	(0.0385)	(0.0333)	(0.0286)	(0.0260)	(0.0283)	(0.0285)
Separated	-0.3956***	-0.3706***	-0.2990***	-0.2819***	-0.2428***	-0.1877***	-0.1445***	-0.1451***	-0.1521***
	(0.0989)	(0.0839)	(0.0711)	(0.0619)	(0.0536)	(0.0459)	(0.0418)	(0.0455)	(0.0458)
Divorced	-0.1045	-0.0481	-0.1564**	-0.1683**	-0.1513***	-0.0987**	-0.0468	-0.0129	0.0367
	(0.1067)	(0.0905)	(0.0766)	(0.0668)	(0.0578)	(0.0495)	(0.0451)	(0.0491)	(0.0494)
Widowed	-0.1268	-0.0678	-0.4033***	-0.3815***	-0.3995***	-0.3378***	-0.1710**	-0.2057**	-0.1667**
	(0.1785)	(0.1515)	(0.1282)	(0.1117)	(0.0967)	(0.0828)	(0.0755)	(0.0821)	(0.0827)
Never married and not de facto	-0.0031	-0.0406	0.0288	-0.0263	-0.0351	-0.0792*	-0.0660	-0.0288	0.0802*
	(0.1033)	(0.0876)	(0.0742)	(0.0646)	(0.0560)	(0.0479)	(0.0436)	(0.0475)	(0.0478)
Log household income	0.0242	0.0205	0.0284	0.0135	0.0072	-0.0099	0.0016	0.0183*	0.0107
	(0.0240)	(0.0204)	(0.0173)	(0.0150)	(0.0130)	(0.0111)	(0.0101)	(0.0111)	(0.0111)
Wage rate	0.0005	-0.0009	-0.0000	0.0001	-0.0005	-0.0002	-0.0002	0.0001	-0.0004
	(0.0011)	(0.0009)	(0.0008)	(0.0007)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Education: Grad diploma, grad certificate	-0.0908	-0.0327	-0.1032	-0.1155	-0.1267	-0.1327*	-0.0652	-0.0113	0.0977
	(0.1597)	(0.1355)	(0.1147)	(0.0100)	(0.0867)	(0.0741)	(0.0675)	(0.0734)	(0.0740)
Education: Bachelor or honours	0.0710	0.0784	-0.0806	-0.0549	-0.0202	-0.0339	-0.0772	0.0661	0.0870
	(0.1453)	(0.1233)	(0.1044)	(0.0910)	(0.0788)	(0.0674)	(0.0614)	(0.0668)	(0.0673)
Education: Adv diploma, diploma	-0.1153	-0.1297	-0.1348	-0.1241	-0.1428	-0.1308	-0.1214	-0.0594	-0.0732
	(0.1943)	(0.1650)	(0.1396)	(0.1216)	(0.1053)	(0.0902)	(0.0821)	(0.0894)	(0.0900)
Education: Cert III or IV	-0.1573	-0.0387	-0.0715	0.0629	0.0449	-0.0247	-0.0971	-0.0310	-0.0859
	(0.1810)	(0.1537)	(0.1301)	(0.1133)	(0.0981)	(0.0840)	(0.0765)	(0.0833)	(0.0839)
Education: Year 12	-0.0915	0.0627	-0.0282	-0.0188	-0.0415	-0.0317	-0.0852	-0.0023	0.0318
	(0.1709)	(0.1450)	(0.1228)	(0.1070)	(0.0926)	(0.0793)	(0.0722)	(0.0786)	(0.0792)
Education: Year 11 and below	-0.2322	-0.1607	-0.2997**	-0.1248	-0.1028	-0.0958	-0.1604*	-0.0460	-0.0383
	(0.1967)	(0.1669)	(0.1413)	(0.1231)	(0.1066)	(0.0913)	(0.0831)	(0.0905)	(0.0911)
Children aged 0 – 4	0.0676	0.0372	0.0350	0.0216	-0.0173	-0.0147	-0.0252	-0.0074	-0.0128

	(0.0465)	(0.0395)	(0.0334)	(0.0291)	(0.0252)	(0.0216)	(0.0196)	(0.0214)	(0.0215)
Children aged 5 – 9	0.0211	0.0249	-0.0087	-0.0094	-0.0336	-0.0178	-0.0293*	-0.0260	-0.0211
	(0.0399)	(0.0339)	(0.0287)	(0.0250)	(0.0216)	(0.0185)	(0.0169)	(0.0184)	(0.0185)
Children aged 10 – 14	0.0357	-0.0010	-0.0257	-0.0279	-0.0231	-0.0172	-0.0163	-0.0146	0.0010
	(0.0367)	(0.0312)	(0.0264)	(0.0230)	(0.0199)	(0.0171)	(0.0155)	(0.0169)	(0.0170)
Working hours	0.0025	0.0021	0.0014	-0.0005	-0.0004	-0.0004	-0.0008	-0.0008	-0.0006
	(0.0015)	(0.0013)	(0.0011)	(0.0009)	(0.0008)	(0.0007)	(0.0006)	(0.0007)	(0.0007)
Satisfaction with neighbourhood	0.0546***	0.0529***	0.0424***	0.0363***	0.0294***	0.0217***	0.0194***	0.0199***	0.0124***
	(0.0091)	(0.0078)	(0.0066)	(0.0057)	(0.0050)	(0.0042)	(0.0039)	(0.0042)	(0.0042)
Job satisfaction	0.0992***	0.0959***	0.0863***	0.0702***	0.0625***	0.0486***	0.0419***	0.0392***	0.0351***
	(0.0078)	(0.0078)	(0.0056)	(0.0049)	(0.0042)	(0.0036)	(0.0033)	(0.0036)	(0.0036)
Constant	-3.9198***	-3.2387***	-2.5120***	-1.7421***	-1.0987***	-0.4209***	-0.0830	-0.1613	0.3254**
	(0.3411)	(0.2889)	(0.2442)	(0.2136)	(0.1848)	(0.1583)	(0.1441)	(0.1569)	(0.1581)
Observations	45,427	45,427	45,427	45,427	45,427	45,427	45,427	45,427	45,427
Within R-sq	0.0210	0.0266	0.0311	0.0321	0.0305	0.0279	0.0222	0.0177	0.0113

*Note: Robust standard errors, clustered at the home-job-spell level, are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All models also include year and region dummies.*

TABLE A8: UNCONDITIONAL QUANTILE REGRESSION RESULTS: MALE SAMPLE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	P10	P20	P30	P40	P50	P60	P70	P80	P90
Commuting time	-0.0001	-0.0005	-0.0008**	-0.0010***	-0.0007***	-0.0002	-0.0002	0.0002	0.0004
	(0.0006)	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Share of hours WFH									
0% < Share < 25%	0.0112	0.0088	-0.0119	-0.0165	0.0063	-0.0039	-0.0039	-0.0067	-0.0003
	(0.0356)	(0.0295)	(0.0226)	(0.0193)	(0.0164)	(0.0146)	(0.0146)	(0.0152)	(0.0145)
25% ≤ Share < 50%	-0.0034	-0.0549	0.0714	0.0039	0.0485	-0.0075	-0.0075	-0.0304	-0.0165
	(0.0760)	(0.0631)	(0.0483)	(0.0412)	(0.0350)	(0.0311)	(0.0311)	(0.0325)	(0.0310)
50% ≤ Share < 75%	-0.0497	0.0048	0.0873	0.0811	0.0363	-0.0882	-0.0882	-0.0861	-0.0469
	(0.1327)	(0.1102)	(0.0844)	(0.0720)	(0.0612)	(0.0543)	(0.0543)	(0.0567)	(0.0541)
Share ≥ 75%	-0.0880	0.0654	0.1186	0.0259	0.1014	0.0837	0.0837	0.1047	0.0169
	(0.1545)	(0.1283)	(0.0983)	(0.0839)	(0.0712)	(0.0633)	(0.0633)	(0.0660)	(0.0630)
Age: 25-29	-0.1387*	-0.1386**	-0.0694	-0.0506	-0.0652*	-0.0648**	-0.0648**	-0.0730**	-0.0171
	(0.0729)	(0.0605)	(0.0464)	(0.0396)	(0.0336)	(0.0299)	(0.0298)	(0.0311)	(0.0297)
Age: 30-34	-0.1091	-0.1543*	-0.0253	-0.0481	-0.0828*	-0.1079***	-0.1079***	-0.1208***	-0.0689*
	(0.0988)	(0.0821)	(0.0628)	(0.0537)	(0.0456)	(0.0405)	(0.0405)	(0.0423)	(0.0403)
Age: 35-39	-0.0393	-0.1454	-0.0663	-0.1075	-0.1321**	-0.1646***	-0.1646***	-0.1811***	-0.1455***
	(0.1215)	(0.1009)	(0.0773)	(0.0660)	(0.0560)	(0.0498)	(0.0498)	(0.0519)	(0.0496)
Age: 40-44	-0.0025	-0.1219	-0.0869	-0.1248	-0.1680**	-0.2128***	-0.2128***	-0.2377***	-0.2051***
	(0.1426)	(0.1184)	(0.0907)	(0.0774)	(0.0657)	(0.0584)	(0.0584)	(0.0609)	(0.0581)
Age: 45-49	0.1258	-0.0787	-0.0892	-0.0922	-0.1424*	-0.2089***	-0.2089***	-0.2475***	-0.2103***
	(0.1642)	(0.1363)	(0.1044)	(0.0890)	(0.0757)	(0.0672)	(0.0673)	(0.0702)	(0.0670)
Age: 50-54	0.1153	-0.0269	-0.0935	-0.0935	-0.1541*	-0.2127***	-0.2127***	-0.2490***	-0.2225***
	(0.1875)	(0.1557)	(0.1193)	(0.1017)	(0.0865)	(0.0768)	(0.0768)	(0.0801)	(0.0765)
Age: 55-59	0.1280	0.0225	-0.0421	-0.0696	-0.1334	-0.1936**	-0.1936**	-0.2234**	-0.2074**
	(0.2128)	(0.1767)	(0.1354)	(0.1155)	(0.0981)	(0.0872)	(0.0872)	(0.0910)	(0.0868)
Age: 60-64	0.1887	0.1109	-0.0122	-0.0357	-0.0977	-0.1888*	-0.1888*	-0.2194**	-0.1736*
	(0.2399)	(0.1992)	(0.1526)	(0.1302)	(0.1106)	(0.0983)	(0.0983)	(0.1025)	(0.0978)

Self-assessed health	0.3162***	0.2913***	0.2440***	0.1983***	0.1660***	0.1438***	0.1438***	0.1277***	0.1068***
	(0.0172)	(0.0143)	(0.0109)	(0.0093)	(0.0079)	(0.0070)	(0.0070)	(0.0073)	(0.0070)
De facto relationship	0.0227	0.0182	0.0124	-0.0311	-0.0245	-0.0033	-0.0033	0.0189	-0.0050
	(0.0637)	(0.0529)	(0.0405)	(0.0346)	(0.0294)	(0.0261)	(0.0261)	(0.0272)	(0.0260)
Separated	-0.6369***	-0.4984***	-0.4322***	-0.3072***	-0.1755***	-0.0982**	-0.0992**	-0.1237**	-0.1363***
	(0.1165)	(0.0968)	(0.0741)	(0.0633)	(0.0537)	(0.0478)	(0.0477)	(0.0498)	(0.0475)
Divorced	-0.3226**	-0.3368***	-0.1682**	-0.0145	0.0414	0.0068	0.0068	-0.0232	-0.0084
	(0.1281)	(0.1063)	(0.0815)	(0.0695)	(0.0590)	(0.0524)	(0.0523)	(0.0547)	(0.0522)
Widowed	-0.4070	-0.1182	-0.0949	0.0638	0.1173	0.0988	0.0988	0.0972	0.0149
	(0.3094)	(0.2570)	(0.1968)	(0.1680)	(0.1427)	(0.1278)	(0.1268)	(0.1322)	(0.1262)
Never married and not de facto	-0.1696*	-0.1451*	-0.0872	-0.1438***	-0.1018**	-0.0801**	-0.0831**	-0.0903**	-0.0677*
	(0.0988)	(0.0820)	(0.0629)	(0.0536)	(0.0456)	(0.0404)	(0.0405)	(0.0422)	(0.0403)
Log household income	0.0431*	0.0012	0.0232	0.0238*	0.0159	0.0112	0.0112	0.0232**	0.0124
	(0.0250)	(0.0208)	(0.0159)	(0.0136)	(0.0115)	(0.0102)	(0.0102)	(0.0107)	(0.0102)
Wage rate	0.0017	0.0012	0.0006	0.0002	-0.0005	-0.0005	-0.0005	-0.0003	-0.0004
	(0.0012)	(0.0010)	(0.0007)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Education: Grad diploma, grad certificate	-0.1222	-0.0068	-0.1509	-0.0433	-0.0249	-0.0398	-0.0398	-0.0568	0.0628
	(0.2018)	(0.1676)	(0.1284)	(0.1095)	(0.0930)	(0.0826)	(0.0827)	(0.0863)	(0.0823)
Education: Bachelor or honours	0.0204	0.0913	0.0104	0.0337	-0.0243	-0.01960	-0.0196	0.0162	0.0755
	(0.1744)	(0.1449)	(0.1109)	(0.0945)	(0.0804)	(0.0714)	(0.0714)	(0.0745)	(0.0711)
Education: Adv diploma, diploma	-0.0242	0.0025	-0.1819	-0.1172	-0.0920	-0.0167	-0.0167	0.0061	0.0851
	(0.2196)	(0.1824)	(0.1397)	(0.1192)	(0.1013)	(0.0900)	(0.0900)	(0.0938)	(0.0896)
Education: Cert III or IV	-0.1988	-0.0153	-0.1291	-0.1218	-0.1542	-0.0278	-0.0278	0.0247	0.0409
	(0.2136)	(0.1774)	(0.1359)	(0.1160)	(0.0985)	(0.0875)	(0.0875)	(0.0913)	(0.0871)
Education: Year 12	-0.1649	0.1256	-0.0524	-0.0425	-0.1019	0.0181	0.0181	0.0019	-0.0064
	(0.2020)	(0.1678)	(0.1285)	(0.1097)	(0.0931)	(0.0828)	(0.0828)	(0.0863)	(0.0824)
Education: Year 11 and below	-0.3057	0.0491	-0.0790	-0.0714	-0.1744	0.0128	0.0128	-0.0681	-0.0115

	(0.2329)	(0.1934)	(0.1482)	(0.1264)	(0.1074)	(0.0954)	(0.0954)	(0.0996)	(0.0950)
Children aged 0 – 4	0.0658	0.0955***	0.0411	0.0246	0.0158	0.0074	0.0074	0.0136	0.0003
	(0.0419)	(0.0348)	(0.0266)	(0.0227)	(0.0193)	(0.0172)	(0.0172)	(0.0179)	(0.0171)
Children aged 5 – 9	-0.0183	0.0030	-0.0120	-0.0080	0.0122	0.0028	0.0028	-0.0268	-0.0137
	(0.0378)	(0.0314)	(0.0241)	(0.0205)	(0.0174)	(0.0155)	(0.0155)	(0.0162)	(0.0154)
Children aged 10 – 14	0.0313	0.0402	-0.0091	-0.0247	-0.0112	-0.0124	-0.0124	-0.0047	-0.0145
	(0.0372)	(0.0309)	(0.0236)	(0.0202)	(0.0171)	(0.0152)	(0.0152)	(0.0159)	(0.0152)
Working hours	0.0016	0.0020	0.0004	-0.0005	-0.0017**	-0.0012*	-0.0012*	-0.0015**	-0.0009
	(0.0016)	(0.0016)	(0.0010)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Satisfaction with neighbourhood	0.0481***	0.0540***	0.0378**	0.0280***	0.0261***	0.0169***	0.0169***	0.0196***	0.0089**
	(0.0094)	(0.0078)	(0.0060)	(0.0051)	(0.0043)	(0.0039)	(0.0039)	(0.0040)	(0.0038)
Job satisfaction	0.1122***	0.0981***	0.0843***	0.0724***	0.0592***	0.0415***	0.0432***	0.0417***	0.0304***
	(0.0083)	(0.0069)	(0.0053)	(0.0045)	(0.0038)	(0.0034)	(0.0034)	(0.0035)	(0.0034)
Constant	-3.8446***	-2.6539***	-1.9468***	-1.2338***	-0.6060***	-0.1913	-0.0089	0.0894	0.5597***
	(0.3641)	(0.3024)	(0.2316)	(0.1977)	(0.1679)	(0.1492)	(0.1492)	(0.1556)	(0.1485)
Observations	43,406	43,406	43,406	43,406	43,406	43,406	43,406	43,406	43,406
Within R-sq	0.0215	0.0268	0.0306	0.0293	0.0277	0.0229	0.0229	0.0187	0.0130

*Note: Robust standard errors, clustered at the home-job-spell level, are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. All models include year and region dummies.*

THE UNIVERSITY OF
MELBOURNE

MELBOURNE
INSTITUTE
APPLIED ECONOMIC &
SOCIAL RESEARCH

60
YEARS
IMPACT