Life Course Centre

WORKING PAPER SERIES

No. 2024-34

October 2024

The growing effect of job demands on teacher mental health

Results from a longitudinal national household panel survey

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Research Summary

Why was the research done?

Teacher mental health is an important predictor of student outcomes and workforce retention. Teacher mental health has been declining across the developed world, possibly due to increasing job demands, however the reasons are unclear and such declines have been consistent with declines in the wider population and so may not be related to teaching.

What were the key findings?

We identified a non-linear decline in mental health occurred among Australian teachers after 2011, while the prevalence of high job demands remained stable. The sudden decline appears to be due to increasing sensitivity to the demands of the job among teachers. This clarifies the mental health decline was related to teaching, but not necessarily due to changes in the job demands - instead teachers are more vulnerable to high job demands than previously.

What does this mean for policy and practice?

Our results show teaching has been a demanding job (since at least 2005), but we now have evidence that teacher resilience has changed. Government, schools and researchers could focus on how to understand and improve resilience at multiple levels to help teachers.

Citation

Morris, R.W., Kim, L.E., Milton, A., & Glozier, N. (2024). 'The growing effect of job demands on teacher mental health: results from a longitudinal national panel survey', Life Course Centre Working Paper Series, 2024-34. Institute for Social Science Research, The University of Queensland.

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Acknowledgements/Funding Sources

This paper uses unit record data from the Household, Income and Labour Dynamics in Australia Survey (HILDA) conducted by the Australian Government Department of Social Services (DSS). DOI: 10.26193/YP7MNU. 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. 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).

The growing effect of job demands on teacher mental health: results from a longitudinal national household panel survey

Oct 17, 2024

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Author Contributions: RWM designed and performed the analysis, interpreted the results, and wrote the paper; LK, AM & NG conceived the study, designed the study, interpreted the results and wrote the paper.

Competing Interest Statement: No competing interests.

Classification: Social Sciences/Demography.

Keywords: mental health, workplace, risk factors, job demands, job control.

Abstract

Introduction. Teacher mental health is an important predictor of student outcomes and education workforce retention, and has been declining for some years, exacerbated by the COVID-19 pandemic. The various causes of this trend have been speculated to include a younger, less experienced workforce and increasing work demands. *Method.* We evaluated the trends in teacher mental health (MHI-5 scores) between 2005 to 2022, using data from the annual HILDA survey. We tested whether the trend was due to changes in non-work related factors (i.e., changes in workforce composition), or due to workplace risk factors such as high job demands and low job control. *Results.* Teacher mental health was stable to 2011 then declined from a median of 80 (IQR 68-88) to 76 (IQR 60-97) MHI-5. The decline was not explained by changes in workforce composition. The prevalence of high job demands was stable over this period (53% to 55%) while low job control prevalence increased from 34% to 58%. At the same time, the strength of the association of job demands with poor mental health increased from beta = 1.32 [95%CI -0.45 to 3.09] to beta = 4.91 [3.34 to 6.47], particularly after 2011. *Conclusion.* The decline in mental health from 2011 was explained by increasing teacher sensitivity to job demands rather than an increase in job demands (which remained high but stable from 2005 to 2022). Understanding why teachers appear to be more vulnerable to the high job demands could enhance strategies to support teacher mental health and improve workforce retention.

What is already known on this topic

Teacher mental health has been declining across the developed world, possibly due to increasing job demands, however the reasons are unclear and such declines have been consistent with declines in the wider population and so may not be related to teaching.

What this study adds

We identified a non-linear decline in mental health occurred among Australian teachers after 2011, while the prevalence of high job demands remained stable. The sudden decline appears to be due to increasing sensitivity to the demands of the job among teachers. This clarifies the mental health decline was related to teaching, but not necessarily due to changes in the job demands - instead teachers are more vulnerable to high job demands than previously.

How might this study affect research, practice or policy

Our results show teaching has been a demanding job (since at least 2005), but we now have evidence that teacher resilience has changed. Government, schools and researcher could focus on how to understand and improve resilience at multiple levels to help teachers.

The mental health and wellbeing of teachers is an important predictor of student outcomes, workforce retention, as well as a broader indicator of our socioeconomic priorities [1–6]. Recent changes and challenges to public schooling around the world, including the global COVID-19 pandemic [e.g., 7], have highlighted the connection between job stressors and mental health in teachers (as well as in other public services such as hospitals and nurses) [8].

The prevalence of poor mental health among teachers has been the focus of substantial investigation since the global COVID-19 pandemic; a meta-analysis of 54 studies involving 256,896 teachers across 22 countries estimated the prevalence of stress (62.6%), anxiety (36.3%) and depression (59.9%) among teachers worldwide was very high during 2020/2021 [9,10]. However longitudinal studies of teacher mental health have revealed declines started earlier than the COVID-19 outbreak. For example, a study of multiple household panel surveys in the UK found teachers have been reporting declines in mental health since 2013, along with comcomitant increases in mental illness and antidepressant use [11]. Since then, a qualitative trajectory analysis of teachers in the UK found consistent declines in their mental health during 2020 [12], suggesting the COVID-19 pandemic likely excerbated the ongoing trends in the UK. Likewise in Australia a longitudinal national household panel survey found that teachers' mental health may have begun to decline as early as 2015 [13], and this decline was excerbated during the COVID-19 pandemic in 2020.

Various reasons for the decline have been proposed, such as work demands from increasing pressure on teachers to meet diverse student needs [12,14]; a younger lesser experienced workforce, who face greater challenges in managing classroom demands [14,15], and who also represent a demographic more vulnerable to mental health issues [16]; and systemic issues such as lack of management and administrative support [12,17]. However widespread declines in the mental health of the general adult population in the last ten years have made it difficult to attribute declines among any specific occupational group to work-related factors. For instance, Hoang et al found teacher mental health did not decline significantly more than general employees in the wider population over the same period [13,see also 18]. Likewise, Jerrim et al reported widespread increases in mental health diagnoses and antidepressant use across occupational groups in the UK, consistent with a general increasing willingness to diagnose and disclose mental health problems in the wider population [11].

Regardless of how unique any such declines are to teachers the causes may differ. Changes over time in teacher mental health could be due to (a) changes in composition of the workforce, (b) changes in the nature of teaching, or (c) changes in the vulnerability of teachers. Changes to the workforce composition such as an increasing proportion of young people or women; two demographic groups more likely to report poor mental health, could produce an observed decline in the average level of teacher mental health (without any corresponding changes in individual levels of mental health). Changes in workplace psychosocial risk factors might also explain the decline in teacher mental health. Adverse working conditions, such as high stress environments, high workloads and low employee autonomy, have been identified as risk factors for poor physical and mental health [19–21]. For teachers, specific risk factors can include long working hours, high administrative load and lack of teaching experience [22,23]. The severity of exposure to workplace risk factors is commonly indicated by high job demands and low job control (i.e., low autonomy), the combination of which is known as "job strain" [24]. Workers (including teachers) suffering job strain are at greater risk of anxiety and depression, burnout, reduced job satisfaction, and cardiovascular disease [25,26]. Exposure to workplace risk factors could explain the decline in teacher mental health in at least two ways: The prevalence of workplace risk factors may be increasing (due to job changes, workplace changes, or changes in working conditions), and this would represent changes in the nature of teaching. Alternatively (or in addition), the decline in teacher mental health may be due to increased vulnerability to risk factors already present. For instance, it has been suggested that young teachers have become less resilient to the demands of the workplace since COVID due to the lack of training, remote teaching, and support from coworkers [27,28]. In the UK Jerrim et al concluded teachers were more likely to report mental health symptoms and seek treatment than previously, however this was consistent with trends in other occupational groups and so not unique to teachers or due to work-related factors [11]. Thus increased vulnerability of teachers may manifest in lower average levels of teacher mental health, even if the workplace had not changed and prevalence of workplace risk factors remained constant. The distinction between these two explanations of teacher mental health can be rephrased as whether the teaching job has changed or whether teachers themselves have changed.

Therefore, the aim of the present study was to identify whether the observed decline in the mental health of teachers might be due to (a) broader demographic changes in the sex or age composition of the teaching workforce; (b) changes in the reported exposure to work stressors (i.e., the teaching job has gotten worse); and (c) whether teachers have become more vulnerable or less resilient to such stressors over time.

Methods

In this study, we evaluated the explanatory factors for the long-term trends in the mental health of school teachers using regression models. These models incorporate non-linear trend components in an additive model with penalised smooth terms for time, allowing us to capture non-linear temporal patterns in the data. Importantly, terms for non-work related factors (such as age and sex) and work-related factors (such as job control and job demands) were added consecutively, and the resulting trends were then evaluated for changes in trajectory, which helps us identify which factors were responsible for the observed declines in teacher mental health. Furthermore, we compare the trends observed for teachers with another occupational group - nurses and midwives - who share similar psychosocial workplace demands and comparable levels of average mental health, to help identify occupation-specific effects.

Sample

The Household, Income and Labour Dynamics in Australia (HILDA) Survey, funded by the Australian government, was collected yearly between 2001 to 2022. The sampling frame is a nationally representative probabilistic sample of Australian households which collects information on a wide range of aspects of life in Australia, including health and wellbeing [29]. The longitudinal design included 7,682 households in Wave 1 (66 percent response rate), with 87 percent retention in Wave 2 and over 90 percent retention at subsequent waves. The survey adds children (15-years and above) born to sample members and people who joined or shared a household with a sample member. In Wave 11, an additional 2,153 households were included to correct for population growth and alleviate bias from non-random attrition (n = 4,009) [30]. The focus of this paper is from Wave 5 (2005) to Wave 22 (2022), which contain all 17 items measuring workplace psychosocial stressors (see below).

Occupational definitions by ANZSCO professional codes

Occupation was ascertained by the current occupation response and coded to the Australian and New Zealand Standard Classification of Occupations 4-digit codes (Australian Bureau of Statistics, 2009 ANZSCO First Edition, Revision 1). The two codes for “Primary” and “Secondary” school teachers were used. For comparison, we also included the codes for nurses & midwives (hereon *nurses*), because they exhibited comparable levels of mental health as teachers, along with comparable workforce demographic composition (predominantely young and female).

Outcome - Mental health

The 5-item mental health inventory (MHI-5) is a well-validated instrument for assessing mental health in population research [[31]; [32]; [33]). In Australia it has been used as a proxy for common mental disorders where it has high levels of sensitivity and specificity, particularly for mood disorders [34]. The MHI-5 is collected every year in the HILDA survey, and consists of five items assessing positive and negative aspects of mental health. Respondents are asked to state how often they have experienced each of the following during the past four weeks. The five items were: 1) “Been a nervous person”, 2) “Felt so down in the dumps nothing could cheer you up”, 3) “Felt calm and peaceful”, 4) “Felt down”, 5) “Been a happy person”.

The response to each item is selected from a 6-point scale “All of the time”, “Most of the time”, “A good bit of the time”, “Some of the time”, “A little of the time”, “None of the time”. The summed mental health score was created according to Ware et al [35]. Each response is scored 0 to 5, and items were recoded so that higher scores indicated better mental health. Raw scores were summed across the items and then linearly transformed to a 0-100 scale. In accordance with the manual a person-specific score was estimated in any year on which there were valid responses on three or more items, the average being calculated and applied to missing items [36].

Workplace psychosocial stressors

The workplace psychosocial stressors, which at extreme levels are major risk factors for poor mental health [24], were derived from a set of 17 questions representing *job demands & complexity* (hereon "job demands") and *job control* [37]. The subset of items contributing to each component are shown in the Supplementary A (Tables A1 to A2). We constructed a component score for each person in each year by calculating the (within-person) average of the component items (after reverse scoring the negatively worded items). Missing responses were implicitly imputed by this mean estimation procedure.

Analysis

The prevalence of each risk factor was determined by the proportion of people reporting high job demand, or low job control in each year. All 17 items were only available from Wave 5 onwards in HILDA and thus our analysis covered the period from 2005 to 2022. Fixed thresholds for high and low component scores were defined by the response quartile of each component in the entire employed sample of HILDA (all occupations among all employed people in all seventeen waves), so as to provide a common threshold value across the two professions examined here. Thus the fixed threshold for low job control was a job control score below the first quartile of all job control responses (i.e., < 3.25), and the fixed threshold for high job demand was a job demand score above the third quartile of all job demand responses (> 4.55). Significant linear changes over time in the prevalence of psychosocial stressors were tested in a weighted linear regression (i.e., equivalent to an aggregated linear probability model).

Trends in the mental health of teachers and nurses between 2005 to 2022 were modelled as a smooth function of time for each occupation. The smooth trend for each occupation was estimated by a penalized, non-linear spline function over time (years) in an additive model [38–40]. Both linear and non-linear effects of time were included in Model I, and the resulting smooth trend represented the unadjusted mental health trend over time for each occupation.

We then modelled trends adjusted for the potential confounding effect of demographic shifts. Model II estimated the smooth trend of mental health, after including linear terms for age, sex and job tenure and their interaction with time. Thus this model adjusted for changes in non-work related factors over time. Job tenure was determined from the HILDA variable derived from each persons time with their current employer cross-referenced against any occupation changes since the last interview.

Model III added the effect of job control in addition to the terms described for Model II. Model IV added the effect of job demands in addition to the Model II terms. In both models, the effects of job demands and job control were added as parametric interaction terms, to account for non-linear changes over time. From Models II to IV we produced a smooth trend for mental health, which represented the conditional mental health trend after holding the other terms constant. We present the smooth mental health trends as zero-centered partial effects to allow comparison and identify trajectory differences when the additional variables were held at their mean values. We also produced smooth trends when the negative effect of job demands and job control were removed (by minimizing job demands and maximizing job control).

Temporal changes in the sensitivity of teacher mental health to job demands and job control

The sensitivity of teachers' mental health to job demands and job control was determined by estimating and comparing the absolute slopes ($|\beta|$) of each job component score, from a model predicting mental health

(MHI-5 scores). MHI-5 scores were modelled using an additive model [41,42], with a (penalized) parametric interaction term for each job component score and time (see Supplementary B: Model definitions). We included the effects of both job demands and job control in a single model and present the zero-centered partial effects (i.e., slope) of each stressor when the other stressor is held constant. This allows us to uniquely identify the changing impact of each stressor on teacher mental health over time. The model also estimated the uncertainty around each slope, which results in confidence intervals with close to nominal (frequentist) coverage properties [43,44]. The greater each slope deviates from zero over time ($y = 0$), the greater the sensitivity of mental health (in MHI-5 units) to that particular workplace psychosocial stressor.

Along with comparing the slopes for each job component, we also determined how much variance (R^2) in mental health was explained by both psychosocial stressors in each year. This tells us whether the overall importance of workplace psychosocial stressors for mental health has changed over time.

Results

The number of teachers identified by ANZSCO code in each year ranged from n = 332 (2008) to n = 434 (2011). Nurses ranged from n = 180 (2005) to n = 274 (2020). Teachers were similarly distributed over primary and secondary education sectors, while the geographic distribution favoured city schools over regional and remote schools, and both distributions remained stable between 2005 and 2022. However, teachers had significant increases in education levels, and income (adjusted for 2022 dollars) between 2005 and 2022. Nurses experienced similar increases in education and income between 2005 and 2022 as teachers. Gender, partnership and job tenure showed no differences in either occupation sample over the 18 years. Both occupations remained female dominated, and experienced similar levels as well as significant declines in mental health between 2005 and 2022. The prevalence of low job control increased between 2005 and 2022 among both teachers and nurses. The prevalence of high job demands among teachers was consistently high over the period (greater than 50 percent), whilst an increasing proportion of nurses reported high demands.

Survey results

Table 1. Change in demographic composition between 2005 and 2022

Group	Characteristic	2005[1]	2022[1]	p-value[2]
Teachers	Total	N = 349	N = 413	
	Female	253 (72%)	293 (71%)	0.6
	Age	44 (35, 51)	41 (32, 52)	0.2
	Coupled	260 (74%)	319 (77%)	0.4
	New parent	50 (14%)	79 (19%)	0.078
	Edu			<0.001
	Postgraduate	27 (7.7%)	87 (21%)	
	Graduate diploma	119 (34%)	94 (23%)	
	Bachelors degree	126 (36%)	178 (43%)	
	Year 12	75 (21%)	54 (13%)	
	Year 11 or below	2 (0.6%)	0 (0%)	
	Tenure (years)	9 (3, 18)	8 (3, 17)	0.3
	Sector			0.8

Group	Characteristic	2005[1]	2022[1]	p-value[2]
	Primary	191 (55%)	229 (55%)	
	Secondary	158 (45%)	184 (45%)	
	Region			0.10
	City	225 (64%)	279 (68%)	
	Regional	91 (26%)	83 (20%)	
	Remote	33 (9.5%)	51 (12%)	
	Real household income ($000s)	61 (47, 73)	76 (60, 97)	<0.001
	Mental health	80 (68, 88)	76 (64, 84)	<0.001
	Low job control	111 (34%)	218 (58%)	<0.001
	High job demand	171 (53%)	207 (55%)	0.5
Nurses	Total	N = 180	N = 270	
	Female	165 (92%)	244 (90%)	0.6
	Age	42 (35, 48)	38 (29, 53)	0.2
	Coupled	132 (73%)	192 (71%)	0.6
	New parent	35 (19%)	43 (16%)	0.3
	Edu			<0.001
	Postgraduate	4 (2.2%)	32 (12%)	
	Graduate diploma	42 (23%)	63 (23%)	
	Bachelors degree	84 (47%)	139 (51%)	
	Year 12	38 (21%)	36 (13%)	
	Year 11 or below	12 (6.7%)	0 (0%)	
	Tenure (years)	5 (2, 13)	6 (2, 13)	0.3
	Region			0.8
	City	115 (64%)	180 (67%)	
	Regional	42 (23%)	60 (22%)	
	Remote	23 (13%)	30 (11%)	
	Real household income ($000s)	58 (47, 72)	79 (61, 96)	<0.001
	Mental health	80 (68, 84)	76 (64, 84)	0.012
	Low job control	46 (27%)	99 (39%)	0.010
	High job demand	67 (39%)	151 (59%)	<0.001

[1]N = N; n (%); Median (IQR)

[2]Pearson's Chi-squared test; Wilcoxon rank sum test; Fisher's Exact Test for Count Data with simulated p-value (based on 2000 replicates)

Yearly mental health levels and prevalence of workplace risk factors

Figure 1 presents the mean mental health levels (MHI-5 scores) in each year, along with the yearly prevalence of low job control and high job demands, for each profession. Mental health levels decreased sharply among teachers after 2011, with year-on-year decreases between 2013 to 2021 (see trend analysis below). At the same time, the prevalence of low job control increased among teachers, at an average rate of 1 percent per year ($\beta = 1.13, p < .001$), while prevalence of high job demands increased at less than half a percent ($\beta = 0.45, p = .009$) and so was relatively stable. Among nurses, the increases in prevalence of low job control and high job demands were less than 1 percent per year ($\beta = 0.53, p = .005$ and $\beta = 0.97, p < .001$, respectively).

Figure 1 about here

Trend analysis of mental health from 2005 to 2022

We estimated the total smooth trend in mental health between 2005 and 2022 (Model I), as well as an adjusted trend after taking into account changes in the composition of age, gender ratio, and job tenure over the period as non-work related controls (Model II). These non-work related controls were included because we know that mental health scores of the general population change with age and gender in this data [16], and job tenure is also likely associated with mental health. In addition to these controls, Models III and IV adjusted for the workplace risk factors of job control and job demands respectively.

Figure 2 about here Model I shows the mental health (MHI-5 scores) of teachers and nurses declined over the period, with a significant non-linear change after 2011 ($F_{3.68} = 22.99, p < .001$ and $F_{2.62} = 12.88, p < .001$, respectively). Model II shows that once non-work related factors were held constant then most of the estimated decline among nurses was accounted for ($F_1 = 1.76, p = .17$); while the estimated decline among teachers was still apparent ($F_{3.75} = 10.79, p < .001$). Models III and IV show the estimated mental health decline among teachers was eliminated by adjusting for job control ($F_{1.0} = 1.49, p = .28$) while the estimated decline was not just eliminated but reversed when job demands were removed ($F_{1.69} = 5.67, p = .01$). The trends in nurse mental health remained non-significant ($p = 0.54$ and 0.41, respectively), and a follow-up linear mixed model with random intercepts and effects of time for each participant confirmed the (fixed) linear effect of time was also non-significant for the β_{time} of nurses ($t_{479.8} = -0.86, p = .39$). This suggests that the decline in teacher mental health since 2011 can be explained by psychosocial stressors rather than demographic changes, while the trends in nurse mental health have mostly been due to non-work related factors. However given the minimal change in the prevalence of high job demands among teachers since 2005, the amount of decline in teacher mental health does not appear to be fully-explained by corresponding changes in prevalence of this risk factor. Instead changes in the strength of association between mental health and job demands (or job control) may be responsible, which we examine next.

Temporal changes in the sensitivity of teacher mental health to job demands and job control

We estimated the association of teacher mental health with each psychosocial stressor in a regression model of mental health by year, where the absolute slope of each stressor in each year ($|\beta|$) represents the sensitivity of mental health. Figure 3 presents the changes over time (i.e., in each year) in sensitivity among teachers below. The smooth trend represents the zero-centered penalised partial-effect of each psychosocial stressor on mental health over time, and the solid points represent the unpenalised point estimate in each year. Sensitivity is indicated by the deviation from $y = 0$ in each trend or point in absolute MHI-5 units; where each shaded 95% confidence interval or 95% error-bar excludes zero indicates where teachers became more sensitive to that component over time or in that year.

Figure 3 about here The partial-effects of each psychosocial stressor in Figure 3 show the increasing impact of a 1-unit change in each stressor over time, holding the other stressor constant. As such they show the sensitivity of teacher mental health to job demands increased more than job control, *ceteris parabis*. The inflexion of the increase in sensitivity to job demands after 2011 is consistent with the observed decline in teacher mental health at the same point.

The fit (R^2) of the OLS regression of job components on mental health each year improved from ~4 percent in 2005 to almost ~16 percent by 2022 (see Figure B1 in Supplementary). The improvement in the R^2 suggests that job control and job demands explain an increasing proportion of the variation in the mental health of teachers in the past seventeen years, consistent with increased vulnerability to workplace risk factors.

In combination with the stable rate of prevalence of high job demands over time (Figure 1), this result represents model-derived evidence that the decline in teacher mental health is best explained by changes in sensitivity to job demands among teachers rather than due to changes in the prevalence of high job demands.

Discussion

The mental health of teachers has markedly declined since 2011, and while the the prevalence of stressors has accumulated over years and underscores the growing pressure on the profession, the increases are not sufficient to explain the sharp decline in teacher mental health since 2011. Instead the current findings indicate that the decline in teacher mental health is explained by increased sensitivity to high job demands. By contrast, the mental health decline of nurses was explained by changes in the workforce composition. These findings are important as employee mental health, which can be considered as a type of job resource [45], predicts motivation to leave the profession and employee turnover [6].

One of the most striking findings in the current study is the increasing sensitivity of teachers' mental health to the demands of the teaching job. Despite over half the teachers in the HILDA survey reporting high job demands each year, the impact of this risk factor on mental health only began to intensify after 2011. That is, the same level of job demands that may have been manageable in the past now contribute more substantially to mental health decline among teachers - even while holding the level of job control constant. Typically the level of job control (or coworker support) can act as a buffer against the ill effects of high job demands [24], and we found the reported prevalence of low job control increased over time. Yet the loss of this buffer only partially explained the decline in teacher mental health, and job control did not increase in importance over job demands (see Figure 3).

We found that adjusting for job demands (but not job control) was sufficient to reverse the decline in teacher mental health, suggesting interventions aimed at reducing job demands or increasing resilience to these demands would be particularly effective in improving mental health outcomes. Common job demands in the teaching profession include a high workload and having multiple roles beyond teaching, such as administrative duties and responsibility for student physical and mental wellbeing [12,17]. For example, the UK Government's Department for Education have published guidance and resources to assist schools in reducing workload to improve teacher wellbeing (Department for Education, 2024a). Recommendations to reduce teacher workload included the removal of tasks and activities that do not require teachers' professional skills and judgment (Department for Education, 2024c). Encouraging schools to sign up to the Education Staff Wellbeing Charter was also recommended, which explicitly commit schools to supporting staff wellbeing (Department for Education, 2024b). Schools in Australia and other countries may wish to explore how job demands could be reduced, for example by allowing teachers to focus on teaching more than administrative duties.

Increasing teachers' resilience to job demands could also be effective in supporting teacher mental health. A systematic review on teacher resilience interventions recommended that increasing teacher resilience should be tackled at multiple levels [46]; i.e., person, microsystem, mesosystem, and exosystem, as an individual is a function of multiple levels [47]. For example, improving contextual resources, such as management or coworker support, or creating a trusting and positive school climate, can help increase teacher's resilience (in addition to interventions at the person-level such as mindfulness) [46]. These resources are important buffers of job strain, and may govern whether interventions are successful.

Limitations Despite the longitudinal analysis, our methods are ultimately based on observational data and so the results are correlational and conclusions are descriptive. As such, while policy development must (partially) depend on observational studies, interventions should be developed with caution. For instance, the teacher mental health decline could represent the loss of support or buffers in other (unsurveyed) areas of the workplace (such as coworker support). Unfortunately HILDA does not survey coworker support and so any role in the results reported here must remain subject to future research using other data.

Overall our findings indicate that while the nature of teaching has remained relatively stable, teachers have become more vulnerable to its demands. The decline in teacher mental health has significant implications beyond the individuals directly affected, including students and the wider educational system. Thus, practitioners and policymakers may consider how contextual resources can be provided to reduce job demands and improve teacher resilience, at multiple levels, where teachers can thrive personally and professionally.

Acknowledgments

This paper uses unit record data from the Household, Income and Labour Dynamics in Australia Survey (HILDA) conducted by the Australian Government Department of Social Services (DSS). DOI: 10.26193/YP7MNU. 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. 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).

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Figure 1. Yearly mental health and prevalence of psychosocial risk factors from 2005 to 2022

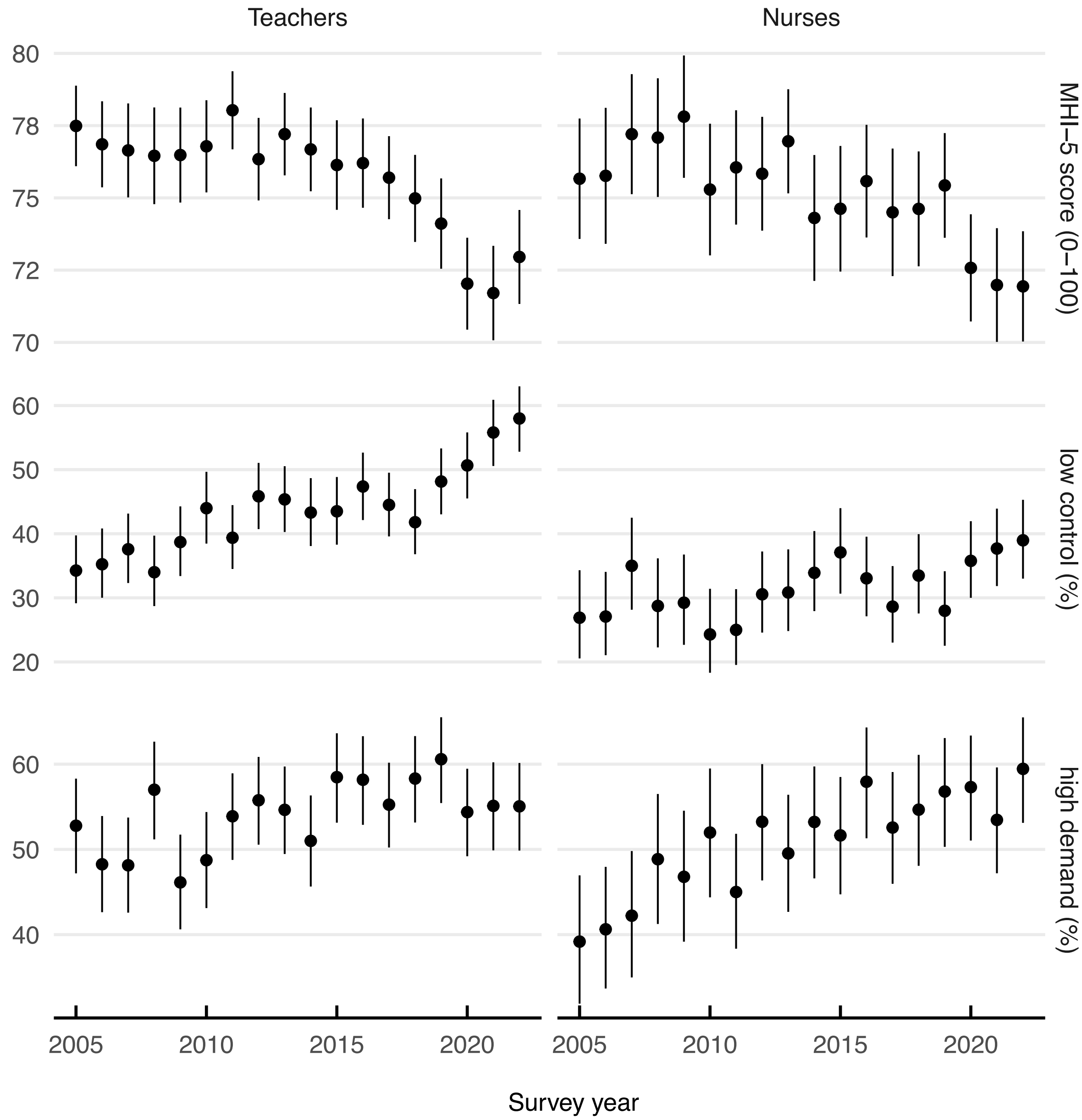

Figure 1 legend. Mean MHI-5 scores (0-100) and prevalence (%) of people reporting *low* job control and *high* job demand in each year (where *high* and *low* are defined by the job component score thresholds between the most extreme quartile of the employed population). Vertical lines represent 95 percent confidence intervals.

Figure 2. Mental health trend analysis partial effects

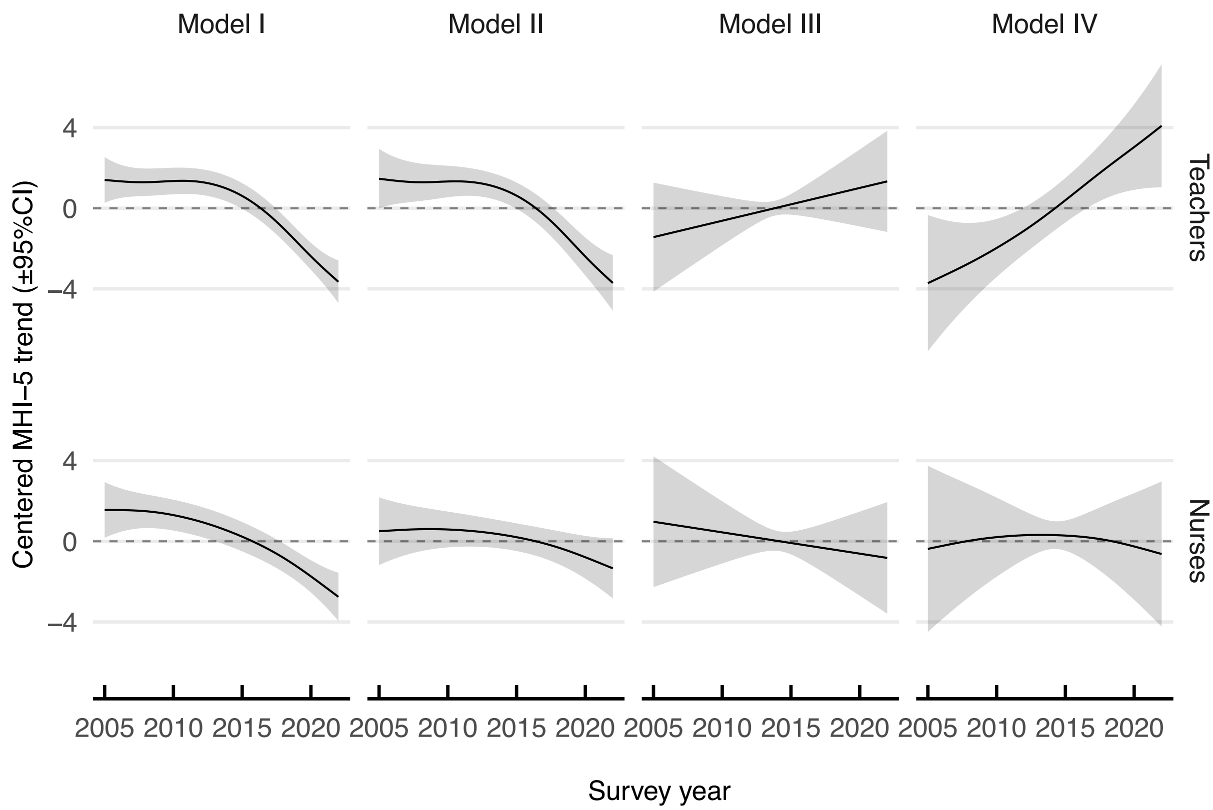

Figure 2 legend. Zero-centered partial effects of year on mental health from each model. Model I is the unadjusted trend over time. Model II is the trend adjusted for non-work related factors (age, sex, length of job tenure). Model III is adjusted for the same non-work related factors as well as job control. Model IV is adjusted for job demands (and the non-work related factors). Shaded areas represent 95 percent confidence intervals.

Figure 3. Sensitivity of teacher mental health to job demands and job control

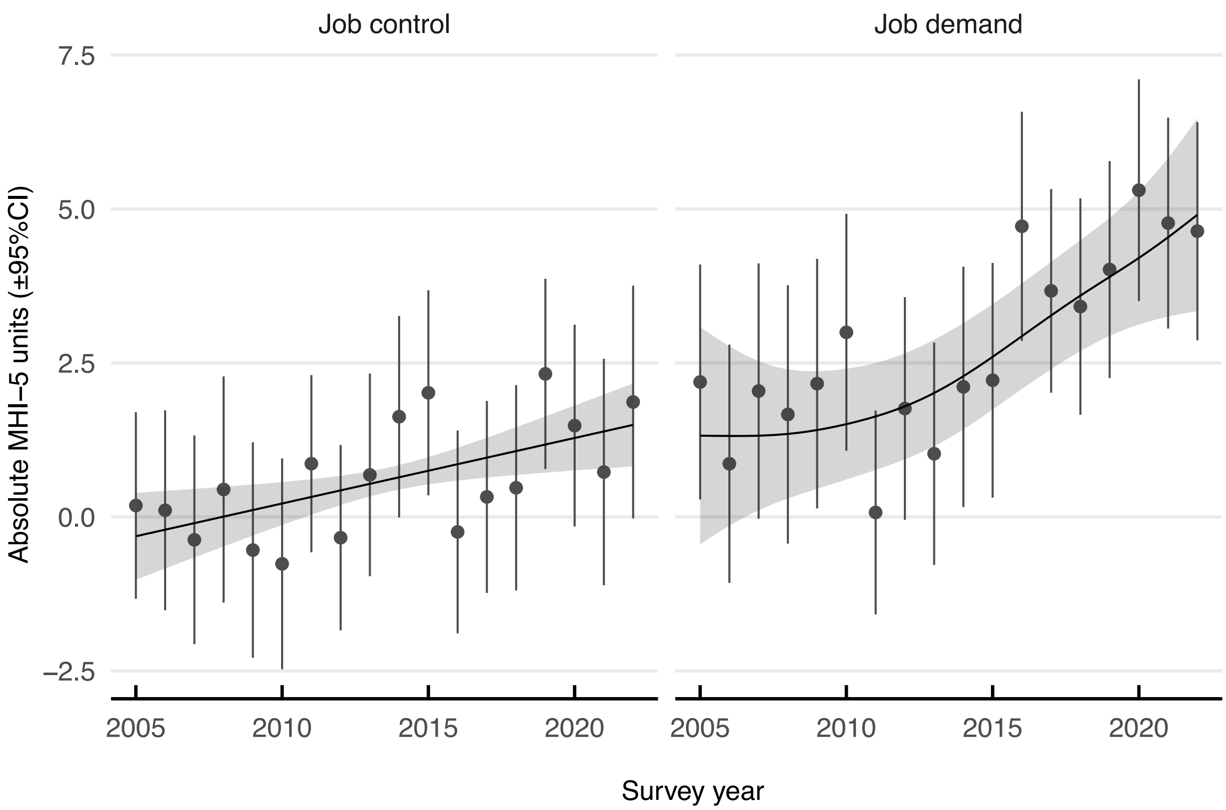

Figure 3 legend. Partial effects of each job component from penalized (smooths) and unpenalized (points) models of teacher mental health, representing sensitivity (in absolute MHI-5 units) of mental health to psychosocial stressors between 2005 and 2022. Shaded regions and vertical lines represent 95 percent confidence intervals.

The growing effect of job demands on teacher mental health: results from a longitudinal national household panel survey

SUPPLEMENTAL MATERIAL

Oct 16, 2024

This file includes:

- Appendices A-C
- Figures B1-C1
- Tables A1-C1

Appendix A. Variable definitions

Many surveys of occupational wellbeing, or items focused on work-related wellbeing tend to produce biased estimates due to self-selection of employees unhappy with their job and seeking to express their concerns or grievances in a single-issue survey response. Even large supposedly 'representative' samples can overrepresent unhappy respondents by more than 2.5 times due to such self-selection incentives into work-related surveys (Chauvenet, Buckley, Hague, Fleming, & Brough, 2020; Goodwin et al., 2013). We used HILDA which does not suffer this problem due its wide topic coverage and probabilistic sampling.

HILDA also incorporates a comprehensive set of questions about other aspects of subjective wellbeing, including life satisfaction. In contrast to mental health, teachers generally report higher levels of life satisfaction and self-worth than other occupations (Hoang, Morris, Naehrig, & Glozier, 2023; Jerrim, Sims, Taylor, & Allen, 2020). Both mental health and life satisfaction are important but distinct components of subjective wellbeing, and the comprehensive instruments in HILDA allowed us to distinguish mental health from these other more cognitive/evaluative dimensions which can depend on social level or stage or life (Diener et al., 2017; Diener, Oishi, & Tay, 2018; Kettlewell et al., 2020). Many conflicting findings in the literature may be a result of comparing or confounding these different constructs.

The job demands component score, where higher scores represent the increasing severity of the psychosocial stressor, was constructed from the average of responses to the nine items below.

Table A1. Job demands & complexity items

Code	Description	Waves
jomms	My job is more stressful than I had ever imagined	1 to 22
jompi	I fear that the amount of stress in my job will make me ill	1 to 22
jomcd	My job is complex and difficult	1 to 22
jomns	My job often required me to learn new skills	1 to 22
jomus	I use my skills in current job	1 to 22
jomini	My job requires me to take initiative	5 to 22
jomfast	I have to work fast in my job	5 to 22
jomwi	I have to work very intensely in my job	5 to 22
jomtime	I don't have enough time to do everything in my job	5 to 22

The job control component score, where lower scores represent the absence of job control and so more exposure to the psychosocial stressor, was constructed from the average of responses to the eight items below.

Table A2. Job control items

Code	Description	Waves
jomfd	I have freedom to decide how I do my own work	1 to 22

Code	Description	Waves
jomls	I have a lot of say about what happens in my job	1 to 22
jomfw	I have freedom to decide when I do my work	1 to 22
jomdw	I have a lot of choice in deciding what I do at work	5 to 22
jomflex	My working times can be flexible	5 to 22
jombrk	I can decide when to take a break	5 to 22
jomrpt	My job requires me to do the same things over and over again	5 to 22
jomvar‘	My job provides me with a variety of interesting things to do	5 to 22

Others have identified job insecurity as an important risk factor and linked with psychological disstress (De Witte & Naswall 2003), however it was not prevalent in our teacher sample and so not featured in this report.

Table A3. Job security items

Code	Description	Waves
jompf	I get paid fairly for the things I do in my job	1 to 22
jomsf	I have a secure future in my job	1 to 22
jomcsb	Company I work for will still be in business in 5 years	1 to 22
jomwf	I worry about the future of my job	1 to 22

Appendix B. Model definitions and R-squared

Longitudinal models of annual change in MHI-5 scores (mental health) were constructed using the set of MHI-5 scores from each individual. MHI-5 scores were person-mean centered by subtracting the individual's mean MHI-5 score from each set to form the response variable (y_{it}), and so estimate the *within-subject effects* of time. The person-mean MHI-5 score was also included as a fixed effect (α_i), to address any time-invariant heterogeneity between people.

Models I to IV of MHI-5 scores included year as linear term as well as a penalised smooth additive term, where y_{it} represents the person-centered MHi-5 score for each person in each year, $f(\text{year}_t)$ is a smooth term to capture the average of the yearly changes in MHi-5 scores using cubic splines.

Model I:

$$y_{it} \sim \alpha_i + \beta_1 \text{year}_t + f(\text{year}_t) + \epsilon$$

Model II added terms for age, sex and job tenure, as well their linear interactions with time:

$$y_{it} \sim \alpha_i + \beta_1 \text{year}_t + f(\text{year}_t) + \beta_2 \text{sex}_i + \beta_3 \text{age}_{it} + \beta_4 \text{tenure}_{it} + \beta_4 \text{age}_{it} \cdot \text{year}_t + \beta_6 \text{tenure}_{it} \cdot \text{year}_t + \epsilon$$

Model III added linear and parametric terms for job control, where $f(\text{year}_t) \cdot \text{job component}_{it}$ represents the parametric interaction between the smooth effect of year and job component score:

$$y_{it} \sim \alpha_i + \beta_1 \text{year}_t + f_1(\text{year}_t) + f_2(\text{year}_t) \cdot \text{job control}_{it} + \beta_2 \text{sex}_i + \beta_3 \text{age}_{it} + \beta_4 \text{tenure}_{it} + \beta_4 \text{age}_{it} \cdot \text{year}_t + \beta_6 \text{tenure}_{it} \cdot \text{year}_t + \epsilon$$

Model IV included linear and parametric terms for job demand:

$$y_{it} \sim \alpha_i + \beta_1 \text{year}_t + f_1(\text{year}_t) + f_2(\text{year}_t) \cdot \text{job demand}_{it} + \beta_2 \text{sex}_i + \beta_3 \text{age}_{it} + \beta_4 \text{tenure}_{it} + \beta_4 \text{age}_{it} \cdot \text{year}_t + \beta_6 \text{tenure}_{it} \cdot \text{year}_t + \epsilon$$

For the sensitivity to workplace risk-factors analysis, a single model regressing mental health (MHi-5 scores) onto each job component (job demand, job control) was estimated:

$$y_{it} \sim \alpha_i + f_1(\text{year}_t) + f_2(\text{year}_t) \cdot \text{job control}_{it} + f_3(\text{year}_t) \cdot \text{job demand}_{it} + \epsilon$$

Where y_{it} represents the person-centered MHi-5 score for each person in each year, $f(\text{year}_t)$ is a smooth term to capture the yearly changes in the average MHi-5 level using cubic splines, and $f(\text{year}_t) \cdot \text{job component}_{it}$ is another non-linear term representing smooth changes in the slope between the standardized job component scores and MHi-5 scores in each year over time.

Figure B1. Proportion of variance explained in teacher mental health (R-squared) by job control (filled) and job demands (empty)

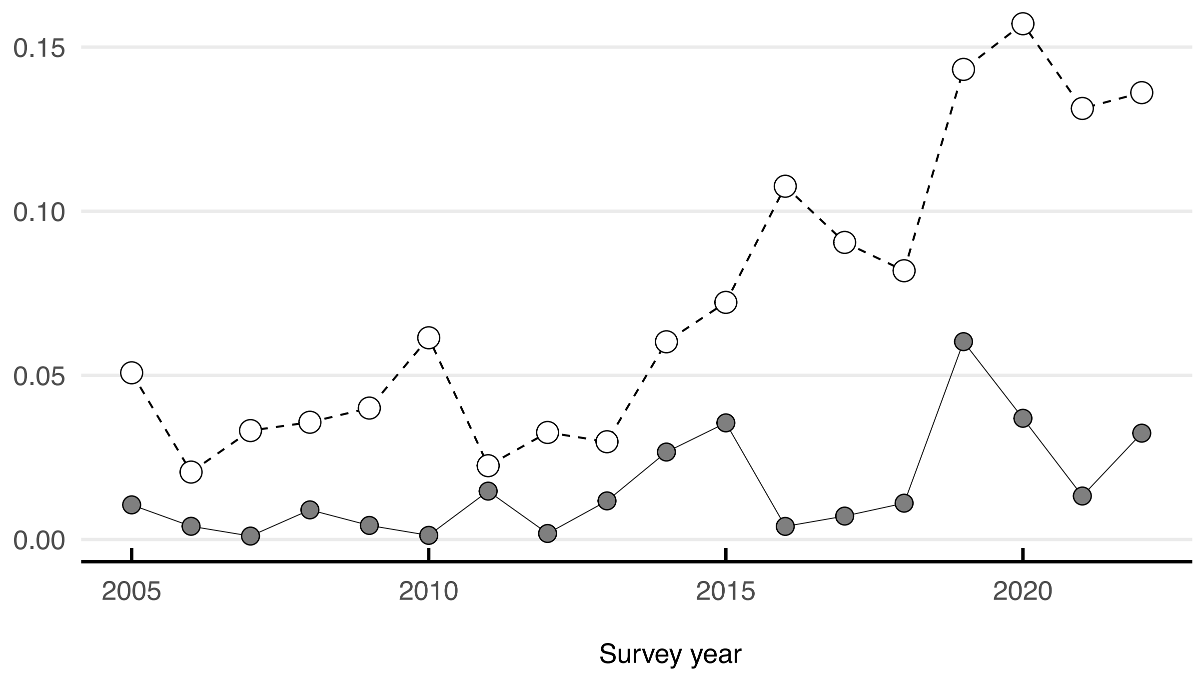

Figure B1 legend. The variance explained by job demands increased over time faster than the variance explained by job control.

Appendix C: State-specific effects

In Australia, state and territory governments are responsible for running schools and setting local policy while the federal government provides the national strategy. For this reason, we considered whether including state effects in the trend models was warranted. State effects were included as separate penalized trends and the variation of each trend was estimated to determine whether it was significantly different from the overall trend. This is similar to deciding whether to include random effects in a mixed model by examining the variation around the random effect. The estimated smooth trends in mental health and the psychosocial job characteristics of teachers for each state and territory are shown below.

Figure C1. Estimated State-specific trends (±95%CI) in teacher mental health

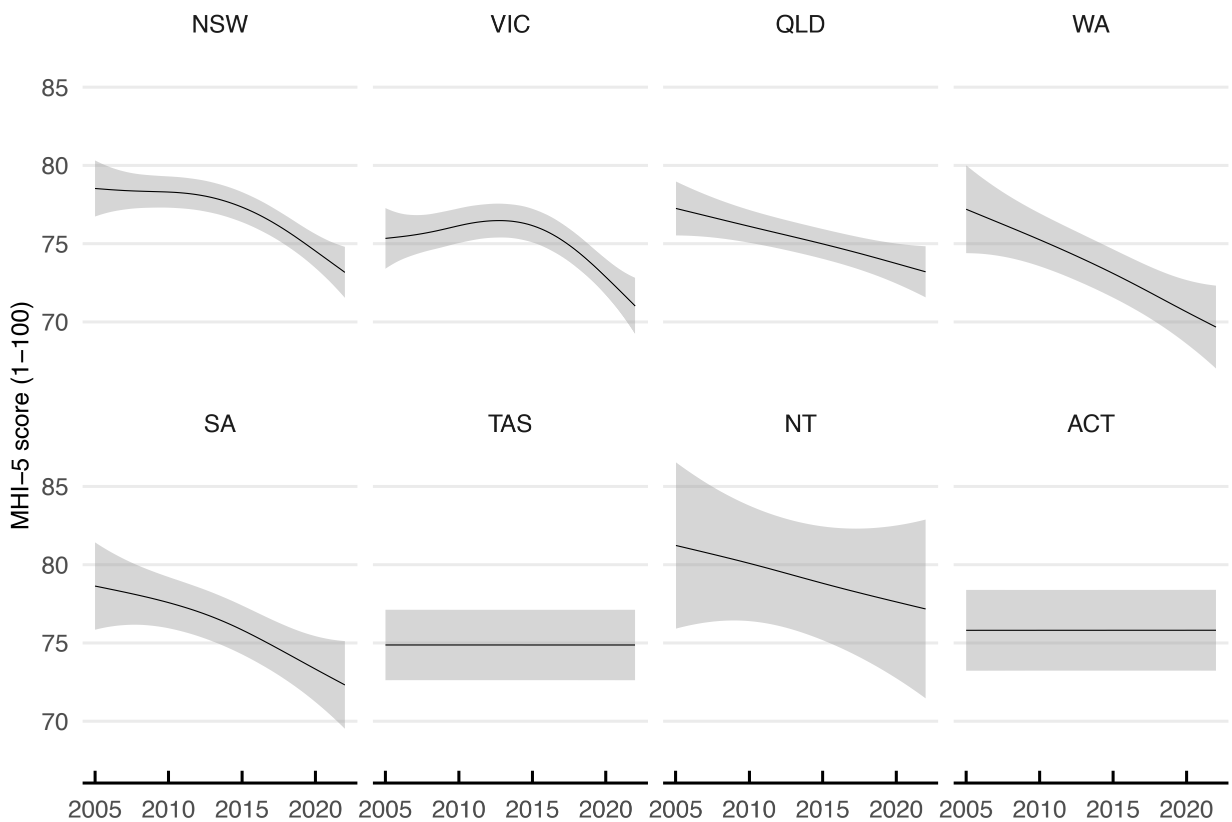

Figure C1 legend. Smooth trends in mental health for each state.

The state model estimated no positive mental health trends among the states, and a declining trend for six states, except for Tasmania (TAS) and the Australian Capital Territory (ACT), which represented less than 5 percent of our sample of teachers ($n = 54$). Table below shows the results of a likelihood ratio test against a null distribution of zero variance for each state, which reveals there was little evidence of any state or territory specific trends (smallest p-value = .061 for WA).

Table C1. Likelihood Ratio Test results for state-specific trends in teacher mental health ($H_0 = 0$ variance)

State/territory	edf	df	statistic	p.value
ACT	0.89	0.89	0.23	0.654
NSW	0.89	0.89	2.06	0.176
NT	3.08	3.80	1.45	0.247
QLD	1.67	2.11	1.39	0.220
SA	0.89	0.89	3.01	0.102
TAS	3.10	3.87	1.73	0.148
VIC	1.10	1.27	0.68	0.355
WA	0.89	0.89	3.94	0.061

*edf: estimated degrees of freedom

The results of a model comparison between a State-specific model and a non-specific model confirmed there was not sufficient evidence to warrant including State-specfic effects as an explanation (Shmueli, 2010). The BIC difference between the two models was 98.2, which is a large difference favouring the non-specific model (Raftery, 1995) and consistent with the non-specific model. The AIC difference between the two models was 1.9, which is a small difference and equivalent to a non-significant difference between models (Raftery, 1995).

Appendix D: Other demographic comparisons (not run)

Table D1. Primary & Secondary teacher differences in 2005 & 2022 Primary school teachers tended to be more female, younger, and less postgraduate qualifications than secondary teachers. This was consistent across both 2005 and 2022.

Table D2. Regional differences in 2022 Primary school teachers in the city were more likely to have a postgraduate degree than regional or remote primary teachers in 2022. No other differences were significant.

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