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A longitudinal analysis of the impact of multidimensional precarious employment on the mental health of men and women

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This study aimed to investigate the effect of precarious employment (PE) on the mental health of Australians. Building on previous research, we conceptualised PE as a multidimensional construct, accounted for gender differences in the associations, and our modelling strategy addressed the possibility of reverse causality bias. Data was pooled panel data from 15 waves (2005–2019) of the HILDA survey (*n* = 14,237). Using PCA, we created two multidimensional measures of PE: objective and subjective. Fixed effects (FE) regression models (attending to unmeasured time-invariant confounders) estimated the change in mental health associated with a change in PE, and instrumental variable (IV) analyses (addressing endogeneity bias) obtained an unbiased estimate of effect of subjective PE on mental health (with ordinary least squares (OLS) models as baseline). For both genders, FE models showed that objective and subjective multidimensional PE both had a strong negative association with mental health (stronger for subjective PE). IV analysis indicated OLS models overestimate the relationship between subjective PE and mental health for men but underestimate it for women, providing causal evidence that subjective PE is important for women's mental health. Overall, findings suggest that targeted PE policies have the potential to provide significant population mental health gains, particularly for working women.

Keywords Employment precarity, Job insecurity, Depression, Gender, HILDA

In recent decades, precarious employment, characterised by unstable and insecure work arrangements, has steadily increased throughout the developed world, including in Australia[1]. Driven by a complex system of social, economic, and political forces, employment precarity has far-reaching consequences[2]. One of the key emerging concerns about precarious employment (PE) is the potential consequences for various facets of individuals' health and wellbeing, particularly mental health. Mental health conditions have increased worldwide over previous decades and are among the leading causes of disability globally[3–5]. Whilst acknowledging mental health is an oft utilised umbrella term encompassing a broad set of disorders, it's use within the context of this study pertains solely to general mental health and wellbeing, inclusive of common mental health disorders such as depression, anxiety, and psychological distress[6,7]. Importantly, social and economic determinants are significant risk factors for common mental health disorders and many of them, such as employment precarity, are potentially modifiable through policy and social reform to effect positive population health improvements[4,5,8].

A negative association between PE and mental health is well established[9,10]. Multiple recent reviews[9–12]have synthesised the substantive extant research in this area and report evidence of an association between various measures of PE and mental health. For example, one review found persistent PE to be associated with 42% increased odds of symptoms of poor mental health[11]. Other reviews have found associations for some measures of PE but not others. For example, negative associations are fairly consistently reported with job insecurity and multidimensional measures of PE, but associations with other PE indicators such as temporary employment or unpredictable working time are often inconsistent or negligible[9,10].

One of the issues pervading the PE scholarship is that there remains no consensus in the literature regarding its definition or measurement[1]. Furthermore, consensus is difficult due to the multifaceted nature of PE differing not only across global regions, between countries and through labour market structures, but over time[1,13].

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Despite this, PE is widely accepted to be a multidimensional and complex concept, involving multiple (and often overlapping) elements of precarity. Indicators or dimensions of PE include job and/or work insecurity, uncertainty, lack of rights and protection, low wages and economic deprivation, and less career advancement opportunities[1,12–14]. Low job control, a lack of recognition and meaning in one's work, powerlessness, and underemployment (such as overqualification or skills misfit) have also been rationalised as possible indicators of PE[3,14–20]. Importantly, in the context of the current study, much of the research to date has conceptualised PE as unidimensional, and it is only more recently that PE as multidimensional construct has been modelled and examined. A 2019 systematic review of the longitudinal research examining PE and mental health suggested that "further single-variable observational studies on job insecurity or temporary employment should *not* be prioritized"[10]. [p.429] The review also found five of the sixteen included studies used multidimensional measures, with meta-analysis finding a much stronger association between poorer mental health using multidimensional exposures of PE[10]. The authors noted that the consistently strong associations found in those studies applying multidimensional exposure constructs suggest that the mental health effects of PE are likely greater than those seen when studying unidimensional aspects of the phenomenon. Moreover, that multidimensional measures "provide a relevant way forward for research in combining subjective and objective parameters to construct more accurate representations of labour market position"[10p.441]. It is also noteworthy that none of the studies (multidimensional or otherwise) in the review were from Australia[10].

Furthermore, the review did not discuss nor stratify analysis by gender, which has been highlighted as an important consideration when examining PE)[14,21]. PE is a highly gendered phenomenon, with women and men differentially exposed to PE across the globe, including in Australia[20,22,23]. Despite women's convergent paid labour force participation rates (8.5% gap in Australia in 2024)[24], their disproportionate time in unpaid work means that they are disproportionately channelled into part-time and casual paid work, and are over-represented in jobs with less pay, less security and poorer conditions compared to men[14,25]. Within Australia, precarity in employment and underemployment is rising[26,27], and given the simultaneous government focus on supporting greater economic gender equality, there is a need for Australian specific understanding of the association between precarious employment and mental health through a gender lens. A recent 2022 study did acknowledge the differential exposure of European women, reporting greater prevalence of multidimensional PE and poor mental health among women, yet found the association between PE and mental health to be stronger among European men[28]. Although this study was cross sectional in nature, it adds to some other evidence (albeit mostly examining unidimensional aspects of PE) suggesting that men may be differentially vulnerable to PE, and/or that women may not be affected at all[9,29–31]. For example, the 2020 systematic review (restricted to Europe) by Utzet et al. found that, of the studies that included gender stratified analyses (less than half of those studies included the review), the gender differences reported were inconsistent, with some studies finding both men and women's mental health to be negatively associated with PE, whilst others reporting this finding only for men[9]. Ultimately, the authors concluded that the evidence was inconclusive and identified a key gap in the PE research, calling for future research to ubiquitously include a gender-sensitive perspective[9].

It is also noteworthy that some earlier European research examined what would also be considered PE but using different terminology; interrogating employment arrangement indicators (contract type, income, irregular and/or unsocial working hours, employment status, training, participation, and representation) in men and women across Europe[32]. This cross-sectional work reported significant associations between low employment quality and poorer mental health for both men and women, with gendered differences least pronounced in earner-carer European nations. To our knowledge, the only Australian research to apply a gender lens and empirically examine multidimensional PE to date is a longitudinal study published in 2023[33]. This study modelled PE as a multidimensional measure based on objective and subjective indicators, examining increasing levels of precarity. The study reported a strong and negative association between PE and mental health in both women and men, across all levels of PE, and with a dose dependent association observed with increasing PE[33].

The mechanisms by which PE impacts a person's mental health are theorised to operate via key stress pathways hypothesised to erode mental health[34–36]. A 2022 scoping review and thematic synthesis of qualitative research on the relationship between PE and mental health suggested that PE leads to stress and negative mental health effects via experiences of financial instability, temporal uncertainty and marginal status (as well as concerns regarding future employment insecurity)[12]. Importantly, much of the research investigating the links between PE and mental health has been cross-sectional in nature which negates any ability to examine temporality in the association. Furthermore, the longitudinal work to date has largely conceptualised and treated the association as unidirectional. However, it is possible that the relationship between PE and mental health is bidirectional, such that those experiencing poorer mental health may be more likely to be selected into PE due to their more limited/constrained options for work and discrimination[37,38]. To date, scant research has explicitly addressed this possible reverse causation (endogeneity) which potentially produces biased estimates of the effect of PE on mental health[1,9]. One exception is a 2016 Italian study that accounted for reverse causation through utility of an instrumental variable (IV) analysis approach to examine the causal effects of temporary contracts on mental health (psychotropic medication prescriptions), reporting the probability of mental illness to be higher among those exposed[39]. Similarly, our current study also employs IV methods (as well as fixed-effects (FE) analysis) to correct for biases caused by the endogeneity of PE. The same methodology was utilised in a recent landmark analysis and publication examining the relationship between physical health and mental health[40]. Widely used in econometrics, IV methodology is considered a quasi-experimental method[41,42], which addresses the bias caused by reverse causality between PE and mental health *before* modelling the effect of PE on mental health (and thus robustly estimating the unbiased of causal effect of PE on mental health).

In summary, whilst a substantial body of evidence has shown a strong link between various aspects of PE and adverse mental health outcomes[9–11,43], there are some limitations in the extant research. Firstly, precarious employment (PE) is often analysed as a unidimensional phenomenon when it is increasingly accepted to be a multidimensional construct[13]. Secondly, causal pathways and endogeneity have not been adequately addressed to date, with further research needed to substantiate causality[43], as well as to account for the reverse causation that exists between employment factors and mental health[1,9]. Lastly, a gender lens is mostly absent from the majority of prior PE research[44]. This study aims to address some of these key gaps and build on the 2023 Australian study examining levels of multidimensional PE and mental health using mixed-effects methodology[33]. Using 15 annual waves of Australian longitudinal data, our key objective is to estimate the causal effect of multidimensional PE on mental health using two empirical methodologies: the FE approach to account for unmeasured time-invariant confounders and an IV approach to address possible endogeneity bias from reverse causation.

Methods

Data source and eligible sample

Following the STROBE guidelines for observational studies[45] (Table S1), this study used data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey, a nationally representative longitudinal study of Australian households with data collected annually (since 2001) from over 7,000 households[46]. To retain population representativeness, a general top-up sample was added in Wave 11, comprising 2,153 households and 5,477 individuals, such that over 17,000 individuals constitute the last 10 waves (2011–2020)[46]. HILDA is a panel data set that collects extensive data on family and labour market dynamics, as well as economic and subjective well-being. Using pooled data from 15 annual waves of HILDA (2005–2019), our population of interest was restricted to employed (wage paid) Australians of working age (25–64 years). Not all items used to construct our PE measure were available in earlier waves (2001–2004). Moreover, whilst wave 20 and 21 of HILDA were available, they were excluded to avoid the possible effect of the COVID-19 pandemic on both employment and mental health. Our final main analytic sample was 14,237 participants (7316 women and 6921 men). See Fig. 1 flow chart for sample selection.

Exposure variable

To capture the multidimensional nature and potential layered effect of employment precarity on mental health, principal component analysis (PCA) was employed to derive an index of multidimensional PE based on five indicators or dimensions of PE. Using a PCA-based approach to create a composite score has been applied previously in the employment quality and PE literature[47,48]. Described in detail in supplementary 2 (and Table S2), the five PE dimensions used to create our PCA multidimensional PE score were: labour force status (part-time or full-time), hours of paid work/week, employment contract (casual, fixed-term, permanent), job security (3 items) and job control (11 items). All variables were derived such that higher numbers or categorical ordering represented less precariousness. In creating our multidimensional PE score, our initial PCA computation revealed two components (out of a possible five) with eigenvalues > 1. Component 1 was informed by the objective measures of PE (hours worked, labour force status and employment contract), whilst component 2

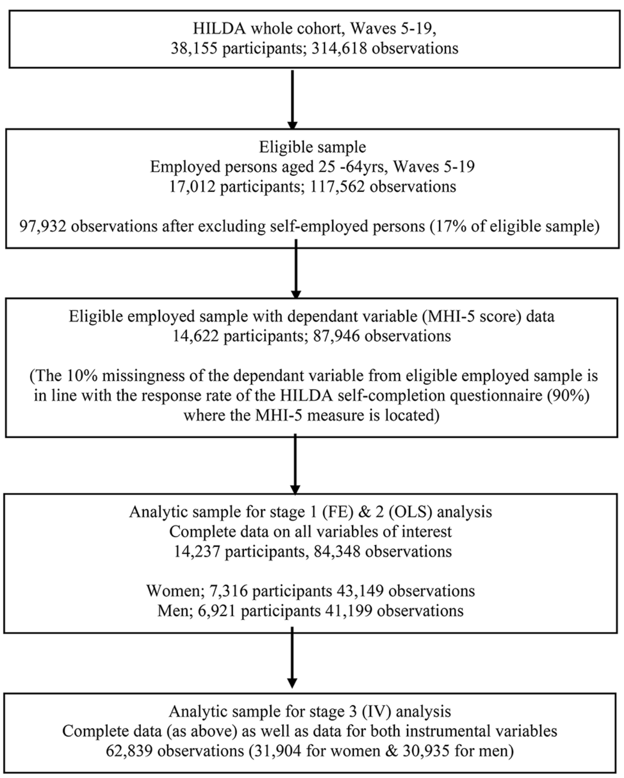

Fig. 1. Flow chart showing selection of analytic sample.

captured the subjective measures of PE (job security and job control). As such, we created two separate composite scores, PE1 and PE2, where PE1 was our objective multidimensional measure, whilst PE2 was our subjective multidimensional measure. Importantly, for both measures, higher scores represented less precariousness.

Outcome variable

Mental health was the outcome examined in this study. Common mental health symptomology and general mental health are captured by population-level studies through a variety of validated self-reported survey measures. The mental health measure utilised in this study was the five-item Mental Health Inventory (MHI-5), a subscale from the Short Form- 36 (SF-36) general health measure in HILDA. With demonstrated validity in the Australian and HILDA context[46,49], the MHI-5 assesses symptoms of depression and anxiety (nervousness, depressed affect) and positive markers of mental health (feeling calm, happy) in the 4-week period preceding the survey[50,51]. The MHI-5 is considered an effective screening instrument for mood disorders or severe depressive symptomatology in the general population and has been validated as a measure for depression using clinical interviews as the gold standard[52–54]. For the purposes of all analyses in this paper, we use the continuous MHI-5 score (expressed on a scale of 0–100), with lower scores representing poorer mental health[50].

Instrumental variables

Our analysis used two IVs in our IV estimation. Whilst frequently used in econometrics, IVs are less common in social epidemiology so are explained briefly here. Notably, an IV needs to meet two conditions: (i) it must be associated with the exposure ("relevance assumption"), (ii) it cannot be correlated with the error term of the outcome (mental health) equation, whereby it can only affect the outcome through the exposure ("exclusion assumption"). Thus, our IV's needed to be associated with PE (our exposure) but not with mental health (our outcome). Our proposed IVs were industry level precariousness (industry-level PE) - which was aggregated from all workers' PE in that industry in a certain year (excluding the individual's PE) - and its lag of this variable. To satisfy the exclusion assumption, the industry-level PE should not directly affect individual mental health. Whilst workers may choose to work in a certain industry based on their health conditions, an individual worker cannot influence that industry's PE (that is, industry level-PE is pre-determined). In other words, the industry level-PE IV is exogenous or orthogonal to the individual mental health. Survey respondent's job industry classification is captured in HILDA at every wave. A derived variable, "current main job industry" is based on the 2006 Australian and New Zealand Standard Industrial Classification (ANZSIC) 2-digit code developed by the Australian Bureau of Statistics (ABS) and captures 96 different industries. We created two industry-level PE IVs for PE1 and two for PE2. Firstly, to derive the total industry-level PE for each exposure measure, we took the mean PE score for that specific PE measure (e.g., mean PE1) by job industry code and by year. Then, we removed the contribution of individual respondent's PE to ensure that the industry-level PE (IV) affects an individual's PE, but not the other way around (that is, individual PE does not affect industry-level PE), naming this the adjusted industry-level PE. Lastly, we generated a lagged variable (prior year) for each of the adjusted industry-level PE variables. The resultant IVs were adjusted industry-level PE1 & adjusted industry-level PE1_lag for PE1 models, and adjusted industry-level PE2 & adjusted industry-level PE2_lag for PE2 models. We conducted IV testing[55,56] to see if our proposed IVs met the IV relevance and exclusion assumptions for their respective PE models. Results showed both IVs were valid instruments for our PE2 model but not for PE1 (see results section and Tables S3a & S3b). Therefore, these two instruments were ultimately used only to estimate an IV model for PE2.

Other covariates

For our FE modelling, we considered the following variables to be independent time-varying plausible common causes of PE and mental health amongst working-age employed Australian adults based on existing literature (and thus included them in our models as confounders): age, household disposable income (quintiles), education, physical health (limiting health condition/not), urbanity (city/regional/remote), and household structure (couple, lone person, with and without dependant and non-dependent children) and time spent in unpaid labour (hours/week). We also controlled for survey year and state of residence to account for contextual, population and/or policy factors that respectively likely change over time or differ between Australian states/territories, and age-squared given age may have a non-linear relationship with our exposure variables over time. In addition to those variables listed above, we also controlled for the time invariant confounder ethnicity (derived 9 category variable accounting for indigenous and non-indigenous Australians as well as other ethnicities) in our Ordinary Least Squares (OLS) and IV models. Importantly, gender was also accounted for in all models given all analyses were stratified by sex.

Statistical analysis

All statistical analyses were performed using Stata 17.0 statistical package[57]. Descriptive analysis was performed to examine sample characteristics, followed by our empirical analysis. Firstly, we conducted separate FE regression models to estimate the change in mental health associated with a change in objective PE and subjective PE for both women and men. In FE models, time-invariant confounding (e.g., personality characteristics such as negative effect that could cause dependent misclassification bias) is effectively controlled for, with each person serving as their own control[58]. This is often referred to as a within-person effects analysis. These models were adjusted for the time-varying covariates considered confounders in this association. In the second part of our analysis, OLS modelling was employed as a precursor for the IV analysis, providing a baseline estimate of the relationship between our two measures of PE (objective PE and subjective PE) and mental health. OLS provides a between-person estimate of the association between the exposure and outcome of interest. However, due to the potential reciprocal relationship between PE and mental health, OLS estimates are likely biased. The

IV approach addresses this endogeneity, obtaining an unbiased estimate of the relationship between PE and mental health when it is suspected that the main exposure (PE) is correlated with the error term of the model (see supplementary file 3 for statistical equations)[41,56]. IV models are considered quasi-experimental such that, similar to a controlled experiment, the sample population is divided into treatment and control subgroups that share the same values for unobserved attributes, with the IVs only affecting the treatment group[41]. In the IV regression, the instruments are used to predict PE in the first stage, and this predicted PE is then used to estimate the causal effect of PE on mental health. For our IV analysis, as per previous applications[59], we employed the limited information maximum likelihood (LIML) estimator, which has been shown to be more robust than the two-step generalised method of moments (GMM)[41,56]. Importantly, the validity of the IV estimator relies heavily on key assumptions. Therefore, we conducted a series of IV testing including weak instrument, weak identification, over-identification (exclusion assumption) and endogeneity tests to determine if our proposed instruments were valid[56,60]. Following verification of IV validity, IV LIML analysis using Stata command *ivreg2* was performed to examine the effect of PE on mental health for both women and men.

Results

Descriptive statistics

Table 1 presents the descriptive statistics for the key variables used in our analysis, stratified by gender. The mean age for women was 43 years and for men 42 years. Men had slightly better mean mental health scores than women (mean MHI-5 score being 76 and 74 respectively). Women spent considerably more time in unpaid labour (mean of 31 h/week) than men (mean of 21 h/week). More women (6%) were heading a lone parent household with children under fifteen compared to men (1%), whereas more men were in couples with children under fifteen (38%) than women (31%). Regarding the employment characteristics that informed the PE measures (operationalised as our exposure variable), key gender differences were also evident. Noting that 100% of the people in the sample were employed, on average, women's mean paid hours per week (33 h/week) were less than men's (43 h/week), evidenced also by the considerably higher representation of women in part-time employment (43%), compared to only 9% in men. More women than men were also employed on casual and fixed-term contracts, such that only 72% of women had permanent ongoing employment, compared to > 80% of men. Mean job security and job control scores were similar for both genders. These employment variable trends were reflected in the mean values for the multidimensional PE measures.

Empirical regression models

FE estimation (model 1)

Table 2 displays the adjusted coefficients derived from linear FE regression models that investigate the relationship between objective multidimensional PE and subjective multidimensional PE and mental health among both women and men. With higher PE scores representing lower precariousness, these within-person models indicate that for both PE measures lower employment precarity is associated with better mental health for individuals of both genders. The effect estimates for the subjective PE measure were larger for both women (β = 1.86, 95%CI 1.68–2.03) and men (β = 2.04, 95%CI 1.85–2.24) compared to those for the objective measure (women β = 0.41, 95%CI 0.24–0.58; men β = 0.75, 95%CI 0.54–0.97). FE results for multivariate associations are presented in Table S4.

OLS estimation (model 2)

Table 2 also presents the adjusted coefficients from the OLS regression models examining the relationship between our two PE measures and mental health in men and women. As aforementioned, OLS models give a 'first impression' or baseline estimate for the between-person association between exposure and outcome. The OLS results show a significant association for objective PE and subjective PE and mental health for both genders. Like the FE results, the subjective PE measure estimates were larger for both men (β = 4.03, 95%CI 3.85–4.21) and women (β = 3.51, 95%CI 3.31–3.72) than the objective PE measure estimates (women β = 0.57, 95%CI 0.41–0.72; men β = 1.80, 95%CI 1.58–2.01). OLS results for covariate associations can be seen in Table S4.

IV estimation (model 3)

Complete results of our validity testing of proposed IVs are presented in supplementary file 3. Table S3a presents IV testing results for our objective PE measure and Table S3b for our subjective PE measure. For each model, the robust LIML estimator (including all confounders) was firstly run for each proposed instrument separately, to diagnose their individual validity. This was done for both the male and female sample separately. Testing identified that the proposed variables (adjusted industry-level PE and its lag) were weak instruments in the objective PE model (Table S3a). Whilst they met the relevance assumption, they performed inadequately against the endogeneity testing, ultimately negating their utility and subsequent IV model for our objective PE measure. In contrast, for our subjective PE models, test results showed that the instruments were valid IVs (Table S3b). The adjusted industry-level PE (and its lag) were individually shown to be good predictors of subjective employment precarity, meeting the relevance assumption, with all models producing a high first-stage F-value, and Wald F statistics greater than the critical value (10% maximal LIML size). Moreover, the endogeneity test results rejected the exogeneity of subjective PE (PE2) when using adjusted industry-level PE (and its lag) as instruments for individual subjective PE (see Table S3b). Lastly, the Hansen J (over-identification) test results show that the instruments meet the exclusion or orthogonal assumption (columns 3 and 6, Table S3b). This indicated that the instruments were valid. Given the testing results above, IV analysis proceeded only for the subjective PE models (for men and women) using model specification as seen in columns 3 and 6 of Table S3b.

Table 2 presents the estimated coefficients from the IV analysis for subjective PE. For women, the IV analysis indicated a larger effect estimate of subjective multidimensional PE on mental health (β = 5.98, 95%CI 3.79,8.18)

	Women	Men
Participants, n (%)	7,316 (51)	6,921 (49)
Observations, n (%)	43,149 (51)	41,199 (49)
Age (years), mean ± SD	42.7 ± 10.8	42.1 ± 10.8
Mental health, MHI-5 score, mean ± SD The MHI-5 is expressed on a 0-100 scale, with lower scores indicating poorer mental health	74.3 ± 16.1	76.0 ± 15.5
Total unpaid labour (hours/week), mean ± SD	30.8 ± 24.3	20.6 ± 15.9
Household structure, n (%)		
Couple no children	12,149 (28.2)	11,317 (27.5)
Couple with children < 15	13,235 (30.7)	15,737 (38.2)
Couple with children > 15 (dependent students or non-dependent children)	6,069 (14.1)	5,449 (13.2)
Lone person	5,245 (12.2)	5,779 (14.0)
Lone parent with children < 15	2,585 (6.0)	388 (0.9)
Lone parent with children > 15 (dependent students or non-dependent children)	2,212 (5.1)	1,037 (2.5)
Other (other related no children < 15, group household unrelated, multi-family)	1,654 (3.8)	1,492 (3.6)
Education, n (%)		
School not completed	7,540 (17.5)	6,302 (15.3)
Year 12	5,153 (11.9)	5,103 (12.4)
Diploma/Certificate	13,142 (30.5)	16,783 (40.7)
Bachelor's degree and above	17,314 (40.1)	13,011 (31.6)
Ethnicity		
Non-indigenous Australian	33,786 (78.3)	32,009 (77.7)
Indigenous/Torres Strait Islander Australian	830 (1.9)	724 (1.8)
New Zealander	990 (2.3)	1,318 (3.2)
European	3,434 (8.0)	3,463 (8.4)
Middle East & North Africa	189 (0.4)	319 (0.8)
East & Southeast Asia	2,092 (4.9)	1,272 (3.1)
South & Central Asia	647 (1.5)	978 (2.4)
America	684 (1.6)	496 (1.2)
Central & Southern Africa	497 (1.2)	620 (1.5)
Household disposable Income, quintiles, n (%)		
1st quintile	1,851 (4.3)	1,311 (3.2)
2nd quintile	5,479 (12.7)	5,416 (13.2)
3rd quintile	9,670 (22.4)	9,208 (22.4)
4th quintile	12,588 (29.2)	12,067 (29.3)
5th quintile	13,651 (31.4)	13,197 (32.0)
Long-term health condition, disability, or impairment, n (%)		
Yes	7,562 (17.5)	6,745 (16.4)
No	35,587 (82.5)	34,454 (83.6)
State, n (%)		
New South Wales	12,093 (28.0)	11,748 (28.5)
Victoria	11,297 (26.2)	10,551 (25.6)
Queensland	9,233 (21.4)	8,739 (21.2)
South Australia	3,842 (8.9)	3,516 (8.5)
Western Australia	3,758 (8.7)	3,855 (9.4)
Tasmania	1,456 (3.4)	1,293 (3.1)
Northern Territory	451 (1.1)	392 (1.0)
Australian Capital Territory	1,037 (2.4)	1,105 (2.7)
Remoteness of residence, n (%)		
Major city	28,393 (65.8)	27,226 (66.1)
Regional/rural	14,155 (32.8)	13,381 (32.5)
Remote	601 (1.4)	592 (1.4)
PE dimensions used to create PE measures		
Hours worked/week in all jobs, mean ± SD	33.27 ± 12.5	43.05 ± 10.7
Labour force status, n (%)		
Full time worker	24,420 (56.6)	37,415 (90.8)
Part-time worker	18,729 (43.4)	3,784 (9.2)
Continued		

	Women	Men
Employment contract, n (%)		
Casual	7,475 (17.3)	4,329 (10.5)
Fixed-term contract	4,758 (11.0)	3,729 (9.1)
Permanent/ongoing employment	30,916 (71.7)	33,141 (80.4)
Job security score, mean ± SD (out of a possible 21 where higher numbers represent higher security)	16.27 ± 3.8	15.70 ± 3.8
Job control score, mean ± SD (out of a possible 77 where higher numbers represent higher control)	47.50 ± 11.6	49.13 ± 11.7
PE measures		
PE1(objective multidimensional measure), mean ± SD	-0.2 ± 1.4	0.8 ± 1.0
PE2 (subjective multidimensional measure), mean ± SD	-0.01 ± 1.1	-0.02 ± 1.1

Table 1. Sample characteristics of analytic sample (reported as observations).

Precarious employment (PE)	Mental Health (MHI-5) Score b coefficient^ (95% CI; *p*-value)					
	Women			Men		
	Model 1 - FE	*Model 2 - OLS*	*Model 3 – IV*	*Model 1 - FE*	*Model 2 - OLS*	*Model 3 – IV*
Objective multidimensional PE (PE1)	0.41 (0.24, 0.58) $p<0.001$	0.57 (0.41, 0.72) $p<0.001$	n/a	0.75 (0.54, 0.97; $p<0.001$)	1.80 (1.58, 2.01; $p<0.001$)	n/a
Subjective multidimensional PE (PE2)	1.86 (1.68, 2.03) $p<0.001$	3.51 (3.31, 3.72) $p<0.001$	5.98 (3.79, 8.18) $p<0.001$	2.04 (1.85, 2.24) $p<0.001$	4.03 (3.85, 4.21) $p<0.001$	-0.04 (-1.36, 1.29) $p=0.956$

Table 2. Relationship between multidimensional precarious employment and mental health in working-age adults (25–64) over 2005–2019 by gender: FE, OLS, and IV analysis. Model 1: adjusted for year, age, age-squared, long-term health condition, education, disposable income, state and territory dummies, remoteness of residence, unpaid labour, household structure. Model 2: adjusted as per model 1, and ethnicity. Model 3: adjusted as per model 2, and utility of instrumental variables; industry-level precarity and lag of industry-level precarity in the first stage. ^ Estimated regression co-efficient or estimated mean difference (MH-5 trans score on a 0-100 scale).

than in the OLS (or FE) model. In contrast, the influence of subjective PE on mental health is no longer statistically significant in the IV model for men (β =-0.04, 95%CI -1.36,1.29). This suggests that OLS model overestimates the relationship between subjective PE and mental health for men (upward biased), while it underestimates the relationship between subjective PE and mental health for women (downward biased).

Discussion

Prior research has consistently shown a negative association between PE and mental health. However, interrogating PE as a multidimensional construct is under-researched, and previous work generally fails to address possible reverse causality bias and explore gender differences in the effect. Using fifteen waves of the HILDA survey (2005–2019), this longitudinal study offers three unique contributions to the literature by: (i) examining two multidimensional measures of PE (objective and subjective), (ii) addressing reverse causation in the relationship between subjective PE and mental health to gain unbiased effect of PE on mental health outcome, and (iii) considering how the effect varies across gender in working-age adults. Overall, we found a strong relationship between both objective and subjective multidimensional measure of PE and mental health in our within-person (FE) models (and our OLS models) for both men and women. More specifically, we consistently found larger effect sizes in the subjective PE analyses. IV analysis was only possible for our subjective PE measure, and results indicated that OLS models overestimate the relationship between subjective PE and mental health for men but underestimate the association in women.

In considering our within-person (FE) results, it is noteworthy that our findings align with similar existing research, whereby PE is detrimental to mental health[9,10,33,61]. Interestingly, but somewhat unsurprisingly, the effect estimates for subjective PE were larger for both genders (compared to those for the objective PE measure). Whilst there are advantages and disadvantages to subjective versus objective measures of PE (and the debate continues), subjective measures are considered to reflect a more nuanced representation of one's own experience of PE[62]. Our results suggest that subjective perceptions of insecurity, uncertainty, and lack of control in one's work may be more detrimental to mental health than objective measures such as hours worked or contract type. Grounded on Jacobson's role theory, scholars in this space have proposed (and found) that the anticipation of harm (i.e. perceived job insecurity) can have health effects as potent as experiencing the harm itself (job loss/unemployment)[63,64]. Nonetheless, prior scholarship suggests that the use of subjective measures of work stressors can lead to an overestimation of the correlation between stressors and dysfunction (in our case mental health dysfunction), whilst the use of objective measures potentially leads to an underestimate of the 'true' correlation[65]. However, the association we find between objective measures and mental health is still important.

This is because even if people subjectively feel that that their employment situation is not too bad (for example due to a cohort acceptance of lesser employment security for example), utility of objective measures can still demonstrate that PE is objectively bad for mental health. Therefore, both are important to consider, and a key strength of our analysis is the examination of both an objective and subjective multidimensional measure of PE, given they provide both complementary and distinctive information about PE and its association with mental health.

Our study also highlighted some important gender differences in the associations between multidimensional PE and mental health. Minimal gender differences were found in our FE models, albeit men's effect sizes were slightly higher than women's. In contrast, the IV models revealed significant effect differences between sexes. Our results suggest that we can be confident in the direction of the effect for women after controlling for endogeneity including from possible reverse causation between subjective PE and mental health. Indeed, it appears OLS models actually underestimate the size of the effect on women's mental health (i.e. when endogeneity of subjective PE was not accounted for). This suggests that subjective PE (job security and job control) may be causally associated with women's mental health. However, subjective PE was not found to be associated with mental health for men. Ultimately, employing IV analysis to examine this relationship has provided new insights with respect to the association between subjective PE and mental health. It has shown key gender differences in the effect; whereby subjective PE appears to adversely affect women's mental health, but not necessarily men's.

Our study is policy relevant given mental health is a leading cause of morbidity and productivity loss[66], and our findings suggest that reducing employment precarity can help improve the mental health of Australian workers. Moreover, our findings are especially timely given precarious and insecure employment has recently been described as being at a "crisis point" in Australia[67]. Importantly, our results confirm the urgent need for policy and social reform to address PE in Australia. Nevertheless, our findings also suggest that a "one size fits all" approach to policy is questionable, particularly as it pertains to gender. Our results confirm that PE is highly gendered, with women not only more likely to be exposed, but that subjective PE (job security and job control) appears to be causally associated with women's mental health, but not men's. Moreover, given the differentially high exposure levels for women, it is noteworthy that the associations we report are relevant to a large proportion of the entire working female population. Whilst further research is required to substantiate our findings, gender specific policies regarding PE, whilst novel, may be more successful in mitigating the mental health impact of PE.

This study has several limitations. Firstly, as our multidimensional PE measures were constructed from job-related variables, our analysis only included employed people. This has important implications especially for women, given it is very common for Australian women to move in and out of employment during prime-working years (due to unpaid care demands)[21], and thus we acknowledge an important subset of women, who are not employed, are not captured in our study. Moreover, restricting the sample to only the employed also misses those who leave employment due to impact of PE on mental health. As such, our results could be biased by a selection effect where people who were in PE with the worst impacts on mental health are no longer employed. We also acknowledge that confining our sample to employed people influences our sample characteristics. For example, those with higher education and household income are likely overrepresented in a sample confined to employed people, whilst people with long term health conditions are likely underrepresented. Furthermore, despite HILDA being a nationally representative cohort of the Australian population, it does have some limitations with respect to generalisability to the Australian population at large. Whilst attrition rates are low - with more than 90% of respondents in any wave responding in the next wave[68]- the overall attrition in HILDA is not random. Attrition rates are higher amongst younger participants (15–24 years), single persons, people born in a non-English speaking country, those identifying as Aboriginal or Torres Strait Islander, and people working in low-skilled occupations or who are unemployed[68]. As such, it is likely that the HILDA survey (and this study) underrepresents certain populations.

Secondly, there are some limitations associated with our multidimensional PE exposure measures. Our sample excluded people who were self-employed (17% of the eligible sample - see Fig. 1). This was because the precarity of their self-employment could not be garnered from the data available. Nonetheless, it means that self-employed persons who do experience PE are not accounted for in our sampling. In addition, in the process of building our PCA derived index, we assigned a categorical order to employment contract type, nominating casual employees as the most precarious, followed by fixed-term contracts, then permanent as those with the least PE. Whilst this was the most pragmatic ordering, we acknowledge that not all casual employment in Australia is precarious, and that very short-term fixed contracts could in some instances be more precarious than casualisation. Similarly, long hours of paid work do not necessarily translate to less precarity. In addition, we concede that there are multiple perspectives on what constitutes dimensions of PE, and that the inclusion of job control as an element of PE is a contested space. Whilst it has been argued that low job control and powerlessness (as well as overqualification or skills underutilisation) can be considered possible indicators of PE[3,14–20], others believe job control to be distinct from PE and more a characteristic or byproduct of low-quality employment[69]. A further limitation pertaining to our PE measures is the generalisability and comparability of our study given there is no uniform definition nor measurement tool of multidimensional PE, and employment policies and labour market structure vary widely cross-nationally[12].

Thirdly, given our outcome (MHI-5) and exposure variables (contributing indicators of PE) were self-reported they are susceptible to self-reporting bias such as recall and social desirability biases despite all being either validated or objective measures. Moreover, our subjective PE estimates might be vulnerable to common methods bias resulting in spurious or inflated associations between the exposure and outcome. For example, some individuals might systematically overstate both their subjective precariousness in employment and mental health due to negative affectivity rather than an objective representation of the actual environment. However, given each person is their own reference in the FE models, this problem is minimised for the FE estimates. Nonetheless, given the self-reported subjective indictors of PE are more susceptible to the various measurement biases, it is plausible that the different results between our subjective and objective measures could be driven by measurement biases rather than the underlying constructs.

We also acknowledge that despite gender being universally recognised as a non-binary social construct, the population-based panel data being drawn upon for this study limits our analyses to a binary examination of gender and examining population level differences within and between those who identify as female, and those who identify as male. Lastly, we concede that despite our best efforts, we did not identify valid instruments for our PE1 models (our objective multidimensional measure) and thus were unable to determine if OLS estimates for PE1 were biased or not. Notwithstanding these limitations, this study is the first to investigate the causal effect of a multidimensional measure of PE on mental health, controlling for endogeneity including from possible reverse causation using an IV approach.

Conclusion
Employment precarity is on the rise throughout the developed world, including in Australia, and governments are increasingly concerned about the implications of PE on population health and wellbeing. This study adds to the growing evidence base demonstrating the mental health impacts of multidimensional PE (both subjective and objective) for both women and men. Although our traditional FE and OLS results mirrored earlier findings, our IV modeling approach examining subjective multidimensional PE revealed significant gender differences and increased the certainty of the direction of the effect on women's mental health. This study highlights that more research is required to further examine reverse causation as well as bidirectionality in this association, particularly for men. In addition to gender, it is also pertinent for future research direction to consider other subgroups who are expose to high levels of PE such as migrants. As in many other parts of the world, the results of this study point to the urgent need for policy attention and workplace interventions to address rising PE in Australia, which subsequently have the potential to enact significant population mental health gains.

Data availability
The data that support the findings of this study are not publicly available due to the conditions of data access from the data custodians (the Australian Data Archive). Interested individuals can apply to the Australian Data Archive for access at https://dataverse.ada.edu.au/dataverse.xhtml? alias=ada&q=HILDA, and once approved, can apply to the corresponding author.

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Author contributions

JE and TD conceived and designed the study. JE, TD and YT accessed and verified the data and conducted the data analysis. All authors had full access to the data in the study. All authors interpreted the results. JE wrote the manuscript and compiled all tables and figures. All authors contributed to drafts, approved the final version, and were responsible for the decision to submit the manuscript for publication.

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Declarations

Competing interests

The authors declare no competing interests.

Ethics approval and consent to participate

The HILDA Survey is conducted by the Melbourne Institute of Applied Economic and Social Research at the University of Melbourne on behalf of the Australian Commonwealth Government Department of Social Services (DSS). All respondents provided informed consent to participate in the HILDA Survey. The study was approved by the Human Research Ethics Committee at the University of Melbourne and conformed to the principles embodied in the Declaration of Helsinki.

Additional information

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