Social Science & Medicine 375 (2025) 118073

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Under pressure: Assessing the relationship between job loss and mental health of young adults in Vietnam

Richard Freund [a,b,*], Marta Favara [c], Catherine Porter [d], Douglas Scott [e], Le Thuc Duc [f]

[a] School of Economics, University of Cape Town, Cape Town, South Africa
[b] MIDE Development, Oxford, UK
[c] Oxford Department of International Development, University of Oxford, Oxford, UK
[d] Lancaster University Management School, Lancaster University, Lancaster, UK
[e] Department of Economics and Related Studies, University of York, York, UK
[f] Vietnam Academy of Social Sciences, Hanoi, Viet Nam

ARTICLE INFO

Handling Editor: Social Epidemiology Office

JEL classification:
J6
I1
I3

Keywords:
Mental health
Job loss
Unemployment
Vietnam
COVID-19
Young Lives

ABSTRACT

We examine the association between job loss and mental health among young people in Vietnam using longitudinal data from the Young Lives survey. We exploit the timing of the first severe wave of COVID-19 which occurred between rounds of a phone survey, allowing comparison of pre- and post-wave job status and mental health for the same individuals. Using fixed effects regressions, our findings suggest that job loss is associated with increased levels of anxiety but not depression, in the short run. Specifically, job loss is linked to a 5.9 percentage point (pp) rise in the probability of experiencing symptoms of mild or severe anxiety, nearly double the pre-wave baseline. This association is particularly evident among individuals in the top earnings tercile who no longer live in their natal household, who experience nearly a 17pp increase in the probability of at least mild anxiety. Additional analysis suggests that financial strain and food insecurity may explain just over 20% of the observed associations. These findings highlight the need for targeted mental health and psychosocial support interventions for young people experiencing job loss, particularly among those who are under financial pressure as primary earners in their household.

1. Introduction

Recent evidence documents a vicious cycle between mental health conditions, poverty, and diminished future employment opportunities in low- and middle-income countries (LMICs) (Ridley et al., 2020). Understanding the risk factors of mental disorders in the Global South is therefore crucial to informing policy interventions and helping the most vulnerable avoid a 'psychological poverty trap' (Haushofer, 2019). One such risk factor is job loss, which increased dramatically during the COVID-19 pandemic as economies contracted and businesses shut down (International Labour Organization, 2021a).

Young people are particularly vulnerable to the effects of job loss. First, evidence suggests that youth unemployment rises disproportionately during economic recessions, as firms prioritize retaining older, more experienced workers while younger workers—who have less experience—are the first to be let go (Forsythe, 2022). Second, job loss in early adulthood can have long-term repercussions, known as scarring effects, where periods of unemployment can lead to lower future earnings, reduced employability, and persistent labour market disadvantages (von Wachter and Bender, 2006). These adverse labour market outcomes may, in turn, increase the risk of mental health conditions over time. This risk is particularly concerning given that young adulthood is a critical life stage, often marking the transition to financial and residential independence (Sawyer et al., 2018). Given the scale of job losses during the pandemic, it is critical therefore to understand the mental health consequences of job loss among young people.

Despite a broad literature descriptively documenting that unemployed individuals have worse mental health than those who are employed (Paul and Moser, 2009) — including among youth (Bartelink et al., 2020; Novo et al., 2001) — estimating the effect of unemployment on mental health presents an empirical challenge due to two key issues: reverse causality and selection bias. Reverse causality occurs because poor mental health can itself increase the likelihood of job loss (Peng et al., 2013), while selection bias arises because individuals who lose

* Corresponding author. School of Economics, University of Cape Town, Rondebosch, Cape Town, 7701, South Africa.
E-mail address: FRNRIC009@myuct.ac.za (R. Freund).

https://doi.org/10.1016/j.socscimed.2025.118073
Received 8 November 2024; Received in revised form 20 March 2025; Accepted 10 April 2025
Available online 11 April 2025

their jobs may systematically differ from those who retain employment—not only in observable characteristics, such as education or job sector, but also in unobserved factors such as pre-existing mental health conditions or social support networks (Alloush, 2023). Consequently, cross-sectional studies are highly likely to produce biased estimates.

To address these challenges, the more recent literature has generally relied on two approaches (Cygan-Rehm et al., 2017). The first utilizes longitudinal data to estimate fixed effects models, which account for time-invariant heterogeneity by comparing individuals to themselves over time (e.g., Charles and DeCicca, 2008; Clark et al., 2001). The second approach exploits exogenous variation in employment status, such as mass layoffs, plant closures, or large-scale economic downturns, to isolate job loss that is plausibly unrelated to an individual's pre-existing characteristics (e.g., Alam and Bose, 2022; Marcus, 2013). Generally, these studies find that job loss harms mental health. However, robust research into the effect of unemployment on mental health in LMICs is rare, mainly due to failure to address the reverse causality issue, and limited availability of data on mental health in settings where mental disorders are viewed with social stigma and support is scarce or non-existent.

The mental health impact of job loss may differ in LMICs for several reasons, and the direction of these effects is theoretically ambiguous. One potential reason to expect a greater negative impact in LMICs is the absence of strong social protection systems. Social protection refers to public measures designed to shield individuals from economic and social distress due to income loss, including unemployment benefits and financial support for families. As of 2020, 47% of the total global population were effectively covered by at least one social protection benefit (International Labour Organization, 2021b), but this masks significant inequalities. For example, 84% of the total population in Europe and Central Asia had access, compared to only 44% in Asia and the Pacific. The lack of financial support in LMICs suggests that job loss might have more severe economic consequences, which may, in turn, exacerbate its psychological toll. Conversely, higher churn in the labour market in developing countries, given less stringent regulation (e.g., Kerr, 2018), could mean that job loss is a more routine experience, potentially reducing its negative mental health effects. However, this greater turnover could also have the opposite effect: if job loss is a frequent stressor in LMICs, its cumulative effects may lead to greater chronic anxiety and heightened vulnerability to mental health deterioration.

Finally, potential differences in preferences between high- and low-income countries point to an ambiguous overall direction. A growing literature supports the finding that poorer individuals tend to be more risk averse, as they have little margin for error or loss (Guiso and Paiella, 2008). Therefore, if job loss represents a major financial risk, its psychological impact may be amplified. At the same time, stronger social networks in LMICs may provide informal economic and emotional support, which could buffer against the adverse effects of unemployment (Fafchamps, 2011). For example, evidence suggests that pro-social behaviours are stronger in developing countries (Engel, 2011; Cochard et al., 2021). However, this informal support is unlikely to be a substitute for formal social protection; while it may help cushion the financial blow of job loss, it is unlikely to fully offset the negative consequences of unemployment on mental health.

Against this backdrop, we contribute new evidence on the relationship between unemployment and mental health in Vietnam, a country where mental disorders remain under-researched (Vuong et al., 2011) and stigmatized (Nguyen, 2003). Specifically, we examine the association between job loss during the devastating fourth wave of COVID-19 in 2021 and young people's experiences of anxiety and depression. The pandemic presents a unique opportunity to study these effects, as job losses occurred at an unprecedented scale and speed. Consistent with pre-pandemic research, evidence from high-income countries suggests pandemic-related unemployment negatively affected mental health (e.g., Guerin et al., 2021; Ganson et al., 2021; Witteveen and Velthorst, 2020), yet similar studies in LMICs remain scarce (Posel et al., 2021; Hossain, 2021; Baranov et al., 2022). Furthermore, most studies in LMICs rely on cross-sectional data, making it difficult to disentangle the effects of unemployment from pre-existing mental health vulnerabilities. This is particularly problematic given that vulnerable groups—including women and lower-income individuals—faced disproportionate job losses (Adams-Prassl et al., 2020; Scott et al., 2021), and many already had a higher prevalence of mental health conditions before the pandemic (Collier et al., 2020; Ridley et al., 2020).

We make two key contributions. First, to the best of our knowledge, this is the first study providing robust evidence on the association between job loss and mental health among young adults in a LMIC setting. We use data from a longitudinal cohort study, with mental health outcomes for the same individuals both before and after job loss, to explore this relationship. The timing of the COVID-19 wave was such that it fell between two survey rounds, allowing a before-and-after comparison of the same individuals. We also incorporate individual and survey fixed effects to control for any unobserved time-invariant characteristics that may influence both mental health outcomes and the probability of losing work. Second, we are able to quantify the extent to which perceived financial strain and food insecurity play a role in explaining the negative relationship between job loss and mental health, an important insight for understanding appropriate policy responses.

Vietnam provides a valuable case study for several reasons. While the country was exceptionally successful at limiting the spread of COVID-19 in 2020, the economic consequences of the fourth COVID-19 wave in 2021 were severe: GDP contracted by 6.2% in the third quarter of 2021 (the sharpest decline on record), 4.7 million people lost their jobs, and unemployment rose to 4.0%—the highest increase witnessed in the past decade (see Fig. 1). Youth unemployment, in particular, rose to 8.9%, more than double the statutory working-age unemployment rate, and nearly 2.4 million young people were classified as not in employment, education, or training during this period (General Statistics Office, 2021). Furthermore, existing evidence suggests that mental health conditions are more acute among young people (Le et al., 2012).

2. Methods

2.1. Data

Our data comes from the Young Lives survey, a unique longitudinal cohort study following two cohorts of children in Vietnam. Prior to the pandemic, the children had been visited in person on five occasions since 2002, approximately once every three years, and most recently in 2016. The 2002 sample comprised of 3,000 participants from the provinces of Lao Cai (Northern Mountains), Hung Yen (Red River Delta), Phu Yen (South Central Coast), Ben Tre (Mekong River Delta), and the City of Da Nang. The study sites were selected using a multi-stage sampling strategy to oversample poor households. Hence, Young Lives is not a nationally representative survey. Comparison to national statistics data indicate that Young Lives households are generally poorer than the average Vietnamese household but, despite this, the sample covers the diversity of children in the country in a wide variety of attributes and experiences (Nguyen, 2008).

Following the COVID-19 outbreak, a five-part phone survey was conducted over the course of 2020/21, aimed at measuring the short-term impacts of the pandemic (Favara et al., 2021). At that time, the two age cohorts were between 18 and 19 years old (Younger Cohort) and 25–26 years old (Older Cohort). An initial contact phone call with the Young Lives respondents took place in June–July 2020. The second and third calls took place in August–October and November–December of 2020, while the fourth and fifth calls took place in August 2021 and November–December 2021, respectively.

Attrition rates observed in the Young Lives sample have been relatively low compared to similar long-running studies. In 2016 (the last in-person survey round), the attrition rate was just 5.1%. Furthermore, 88% of the 2016 sample participated in the phone survey, a very low

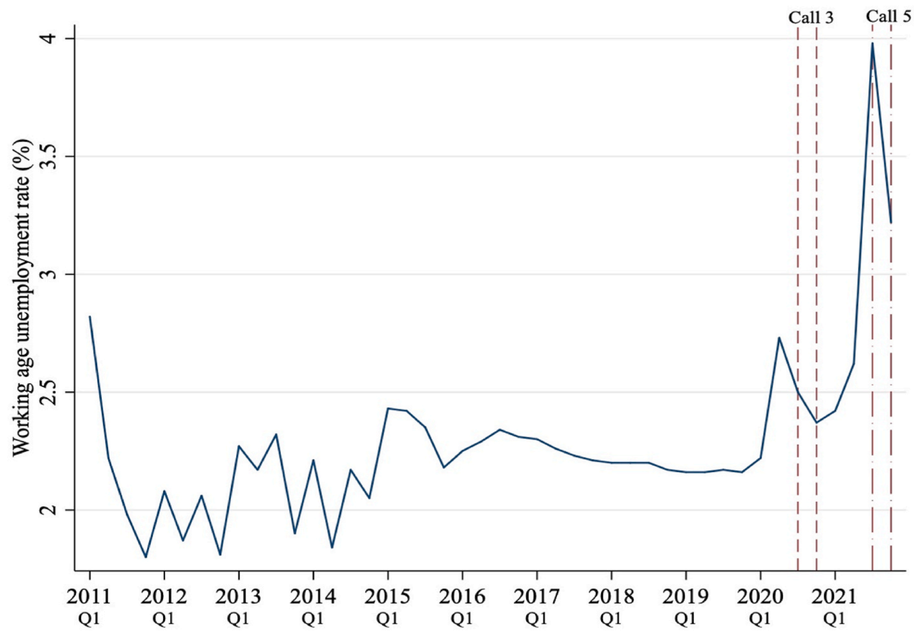

Fig. 1. The statutory working-age unemployment rate (2011–2021) and timings of Young Lives phone surveys
Source: Generated using labour force survey data from the Vietnamese General Statistics Office.
Notes: Statutory working age includes males from 15 to 59 and females from 15 to 54. Call 3 and Call 5 refer to the third and fifth Young Lives COVID-19 phone surveys, respectively.

rate of attrition compared to similar follow-up phone surveys during the pandemic (for example, the UK Millennium Cohort study began at a similar time to Young Lives though only 24% participated in their COVID-19 survey). Males, urban participants, and individuals from poorer households were relatively less likely to participate in the phone survey (Table A.1 in the Appendix provides details on attrition for the Young Lives sample).

During calls 2, 3, and 5, detailed information was also collected on the participant's employment status in the week before they were interviewed. Retrospective information about employment before the pandemic (January–February 2020) was also collected in the second survey call. Given the unprecedented nature and, therefore, salience of the events taking place at the time, we expect any recall error in the binary variable of work status before the pandemic to be negligible. In each time period, we create a dichotomous indicator of work status, defined as working (paid or unpaid) for at least an hour in one's own business, for a household member, or for someone else (during the given reference period). We use this information to create a three-wave panel of observations, in August–October 2020 (call 2), November–December 2020 (call 3) and November–December 2021 (call 5).

To examine the relationship between job loss during the fourth wave of the COVID-19 pandemic and mental health, we restrict the sample to those whose primary activity before the outbreak was working and who maintained employment throughout 2020, here defined as those who were: *i*) working before the pandemic (based on the definition above), *ii*) not enrolled in full-time education at any point during 2020, and *iii*) working in both call 2 (August–October 2020) and call 3 (November–December 2020). This restriction reduces our sample size. Of the 2,363 individuals present in calls 2, 3, and 5, 1,652 were working before the pandemic. Among them, 1,240 were not enrolled in full-time education in 2020. Further restricting the sample to those who were also working in both calls 2 and 3, we retain 78% of individuals in this group. Therefore, applying all restrictions, our final sample consists of 962 individuals. Fig. 2 shows the flow chart of sample restrictions.

2.2. *Mental health outcomes*

In the second, third, and fifth phone surveys, symptoms of anxiety and depression were measured using the Generalized Anxiety Disorder-7 (GAD-7) scale and the Patient Health Questionnaire depression scale-8 (PHQ-8), respectively. The GAD-7 assesses the frequency of seven symptoms of anxiety over the past 14 days, while the PHQ-8 gauges the frequency of eight symptoms of depression over the same time period (the full list of statements is reported in Figures A.1 and A.2 in the Appendix, respectively). The GAD-7 and PHQ-9 have both previously been validated (Zhong et al., 2015; Nguyen et al., 2016) and used in the Vietnamese context (e.g., Collier et al., 2020; Pham Tien et al., 2021). The ninth question of the PHQ (relating to suicidal thoughts) was dropped due to ethical concerns about how to provide support, and the scales were slightly adapted for administration during a phone survey. The adapted questions were piloted prior to the data collection, and the scales were administered as the last section of the survey.

For both anxiety and depression, we create two different dependent variables. First, by summing up the frequency of all symptoms, we generate a continuous raw score, which has a maximum value of 21 for the GAD-7 and 28 for the PHQ-8. Second, we generate a binary variable where 0 indicates no/minimal anxiety (or depression) and 1 indicates the presence of symptoms consistent with at least mild anxiety (or depression). For the binary variables, a cut-off of ≥ 5 was used to represent the presence of "at least mild symptoms" of anxiety (Spitzer et al., 2006) or depression (Kroenke et al., 2009).

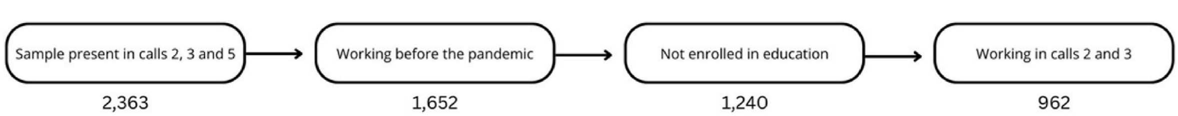

Fig. 2. Flow chart of sample restrictions.

2.3. Covariables

Our key independent variable is a binary indicator for job loss in 2021, which equals one if a participant reported working in call 2 (Aug–Oct 2020) and call 3 (Nov–Dec 2020) but not working in call 5 (Nov–Dec 2021). We also include several control variables, such as whether the participant lived in an urban or rural location and the participant's household size. Additionally, we include binary indicators for other economic shocks experienced by the household since early 2021, including new health expenses, rising food prices, illness, injury, or death of an income-earning household member, natural disasters (e.g., droughts, floods, erosion, frosts, earthquakes), and a decline in farming or business output prices. One limitation is that not all variables are observed in every call. As such, we assume that household size remained constant between calls 2 and 3, and that the prevalence of economic shocks is the same in calls 2 as in call 3. Given the short time period between these calls, and the low prevalence of COVID-19 at the time, we do not feel that these are unrealistic assumptions.

In addition to analysing the full sample, we also examine whether the estimates differ across key subsamples to explore heterogeneity. Specifically, we focus on differences by age (proxied by a binary variable indicating membership in the Older Cohort), monthly earnings terciles from call 2 (Aug–Oct 2020), and whether the participant still lives in their natal household (as a proxy for whether they are likely to be a primary earner in the household).

Lastly, we examine mediating variables that may help explain any relationship between job loss and changes in symptoms of anxiety and/or depression. In particular, we focus on subjective household wealth and food insecurity. Household wealth is measured using a Likert scale, whereby a response of 1 represents 'destitute' and a response of 6 represents 'very rich'. From this, we generated a binary variable which takes the value of one if the participant describes her/his household as 'destitute', poor', or 'struggling', and zero otherwise. Food insecurity is a measure of (at least) mild food insecurity, which takes the value of one if, in the past year, the participant worried that their household would run out of food before they could get money to buy or could acquire more (and zero otherwise).

2.4. Statistical methods

2.4.1. Main empirical estimation model

Our main empirical concerns when estimating the impact of the job loss on mental health are non-random job loss and confounding factors. To address these concerns, we implement several strategies.

First, we recognise that individuals who are employed are likely different from those who are not, even before any job loss occurs. As discussed earlier, to mitigate this potential source of bias, we carefully construct our sample to include only individuals who were working before the pandemic and remained employed throughout 2020. By focusing on individuals who were active in the labour market before the pandemic and consistently employed throughout 2020, we aim to limit the bias that could arise from pre-existing differences between those who work and those who do not, as well as from those who may have lost their jobs at the beginning of the pandemic, when the country was largely unaffected.

Second, we acknowledge that there are likely time-invariant (at least in the short term) individual characteristics, such as gender, education, or underlying health conditions, that might influence both the likelihood of job loss and mental health outcomes. In particular, given the nature of the pandemic, perceived health risks may have directly impacted employment prospects. To address this, we include individual fixed effects, which allow us to control for any time-invariant characteristics that could affect both job loss and mental health outcomes.

Third, we incorporate survey-call fixed effects to control for any factors that vary over time but affect all individuals similarly. The inclusion of these fixed effects allows us to account for changes in the general economic environment and pandemic dynamics that may influence mental health, ensuring that the estimated effect of job loss is not conflated with these broader time trends.

Fourth, in light of the unprecedented nature of the COVID-19 pandemic and its associated economic and health impacts, we control for a host of additional shocks that may have affected mental health outcomes. Specifically, we include controls for the experience of other economic shocks, including new health expenses, rising food prices, natural disasters, or illness of a household income earner. We also control for changes in urban/rural residence and household size. These controls help capture additional stressors that households faced during the pandemic, which could independently affect mental health.

Finally, we conduct several robustness checks. First, to address concerns that the observed effects are not driven by general anxiety related to the pandemic rather than job loss per se, we control for Google Trends data on the search term 'COVID-19 testing' as a proxy for public concern about the virus. Additionally, we control for the cumulative number of confirmed national COVID-19 cases as well as individuals' perceived risk of COVID-19 infection. Second, we apply entropy balancing to reweight the sample, ensuring that key baseline characteristics are balanced between the two groups. Lastly, we apply post-stratification weights for key demographic variables to re-weight the sample such that it matches a nationally representative sample.

We believe that the combination of these strategies substantially strengthens our ability to estimate the causal impact of job loss on mental health. However, we acknowledge that, given the availability of data, the unprecedented nature of the pandemic, and the complexity of factors at play, it is difficulty to rule out all potential confounders. Consequently, we refrain from making definitive causal claims, recognizing the limitations of the data and the broader pandemic context.

Acknowledging this, our empirical strategy is represented as follows (Equation (1)):

$$\textit{Mental health}_{it} = \alpha_i + \varphi_t + \beta \textit{Lost Job}_{it} + \boldsymbol{\rho X_h} + \varepsilon_{iht.} \tag{1}$$

Our outcome variable, *Mental health,* represents the anxiety or depression outcome for individual i in time t. *Lost Job* takes the value of one if the participant no longer reported working in November–December 2021 (and zero otherwise). α_i is an individual fixed effect and φ_t represents survey-call fixed effects. $\boldsymbol{X}$ is a vector of time-varying household-level controls, including urban/rural location, household size, and experience of other economic shocks. The parameter of interest is β, which captures the association between job loss and mental health.

The fixed effects regression framework is easily extended to identify heterogeneity, and quantify whether individuals with certain characteristics are more or less vulnerable to the effects of losing their job:

$$\textit{Mental health}_{it} = \alpha_i + \varphi_t + \beta \textit{Lost Job}_{it} + \delta W_{ih} + \gamma(\textit{Lost Job}_{it} {*} W_{ih}) + \boldsymbol{\rho X_h} + \varepsilon_{iht.} \tag{2}$$

W represents a participant's individual or household characteristic of interest. In particular, we analyse whether the associations of job loss on anxiety differ according to age (proxied by a Cohort dummy variable), call 2 earnings (terciles), and whether the participant still lives in their natal household, captured by whether participants are living with their parents, aunt, or uncle. We use the latter as a proxy for whether participants are likely to be primary earners in their households, under the assumption that individuals who live with their parents, aunt, or uncle are less likely to represent a vital source of income for the household. Indeed, as expected, we find that those who no longer live in their natal household have higher average monthly earnings in call 2 (7,3 million VND compared to 5,8 million VND).

2.4.2. Decomposition of main results

A variety of hypotheses have been offered to explain why job loss may lead to a deterioration in mental health (Price et al., 2002). On the one hand, there is evidence which suggests that the financial strain caused by job loss is the critical mediator in the relationship between unemployment and poor mental health (McInerney et al., 2013; Jones, 2017). However, other research (such as Hetschko et al., 2014; Warr, 1987) argues that job loss produces profound non-pecuniary changes in the life of working individuals, such as loss of structured time, valued relationships, and perceived identity—which also has important detrimental effects on an individual's mental health.

Therefore, after estimating our main results, we use additional regressions to characterise the extent to which any changes in mental health are due to changes in perceived household wealth and food insecurity. To get at the mediation role of financial strain and food insecurity, we employ the following specification:

$$\begin{aligned} \textit{Mental Health}_{it} &= \alpha_i + \varphi_t + \widetilde{\beta}\textit{Lost Job}_{it} + \boldsymbol{\rho X_h} + \tau \textit{Struggling}_h \\ &+ \gamma \textit{Food insecurity}_h + \varepsilon_{iht.} \end{aligned} \tag{3}$$

Struggling is our subjective measure of household wealth, while *Food insecurity* is our measure of mild food insecurity. $\widetilde{\beta}$ is a measure of the association between job loss and anxiety, purged of any effects operating through changes in household wealth and food insecurity. To gauge the importance of the potential channels in explaining the total change in mental health due to job loss, we compare the total effect (β in Equation (1)) with the corresponding $\widetilde{\beta}$ in Equation (3). The difference between the two measures ($\beta - \widetilde{\beta}$) provides an estimate of the effect attributable to the two pecuniary mediators.

3. Results

3.1. Descriptive statistics

Table 1 reports descriptive statistics from our analytical sample. We find that 16.5% of previously employed respondents lost their jobs during 2021, but that there is no statistically significant difference between those who lost their job and those who maintained work according to 2020 anxiety scores and the 2016 Cantril (1965) self-anchoring scale (which asks individuals to visualize a ladder of nine steps, with the bottom step representing the worst life for them and the top step representing their best possible life). We also find that there is no significant difference between the two groups according to changes in 2020 depression scores, although the job loss group had slightly higher levels of symptoms consistent with at least mild depression in November–December 2020. The fact that those who lost their job and those who maintained work are largely similar in terms of mental health outcomes before 2021 is not surprising since reported levels of anxiety and depression among Young Lives respondents in Vietnam during the first year of the pandemic were relatively low (Porter et al., 2022).

The two samples are also similar on all household wealth indicators, the prevalence of other economic shocks in 2021, subjective household wealth, and food insecurity. However, those who lost work are, on average, younger, more likely to be female, have completed fewer years of education, less likely to have had health insurance, less likely to still be living in their natal households, and earned significantly less in August–October 2020. This is in line with international evidence that vulnerable groups were disproportionately affected by pandemic-related job losses (e.g., Adams-Prassl et al., 2020). Previous research using the Young Lives data finds that women, younger participants, and relatively poorer individuals had significantly higher rates of mental health conditions in 2020, further implying that a naïve cross-sectional analysis of the effect of job loss on mental health may be biased (Porter et al., 2021).

3.2. Main results

Table 2 shows the average associations between job loss and mental health. We find that losing work during the pandemic is associated with a significant increase in young people's symptoms of anxiety, but not depression. More specifically, job loss is associated with a 5.9 percentage point (pp) increase (95% CI: 0.3, 11.5) in the probability of experiencing symptoms of at least mild anxiety (a 0.27 standard deviation (*SD*) increase). This represents a 115% increase relative to the average prevalence among the sample in November–December 2020.

The fact that anxiety is associated with job loss in the short-term, but not depression, is not necessarily surprising, as existing evidence suggests that there is typically a sequential relationship between the emotions such that depression comes after anxiety (Boland and Keller, 2009; Fava et al., 2000). Anxiety is often more reactive to sudden, acute stressors, whereas depression is a condition that develops over time,

Table 1
Descriptive statistics.

	Maintained work in 2021 (mean)	Lost work in 2021 (mean)
Individual characteristics		
Age (in years)	22.84	21.60***
Older Cohort	0.60	0.41***
Female	0.42	0.56***
Completed years of education	10.91	10.17***
Self-employed (Nov–Dec 2020)	0.20	0.17
Health insurance (Aug–Oct 2020)	0.42	0.35*
Monthly earnings, million VND (Aug–Oct 2020)	6.54	5.41***
At least mild anxiety (Nov–Dec 2020)	0.05	0.07
Change in GAD-7 raw score (Aug–Oct to Nov–Dec 2020)	−0.44	−0.53
Change in proportion with at least mild anxiety (Aug–Oct to Nov–Dec 2020)	−0.03	−0.03
Cantril self-anchoring scale (2016)	5.66	5.56
At least mild depression (Nov–Dec 2020)	0.05	0.08*
Change in PHQ-8 raw score (Aug–Oct to Nov–Dec 2020)	−0.28	−0.31
Change in proportion with at least mild depression (Aug–Oct to Nov–Dec 2020)	−0.02	−0.01
Household characteristics		
Wealth index tercile 1 (poorest, 2016)	0.42	0.47
Wealth index tercile 2 (2016)	0.37	0.31
Wealth index tercile 3 (2016)	0.22	0.22
At least struggling (Aug–Oct 2020)	0.08	0.09
Worried about running out of food in past year (Nov–Dec 2020)	0.16	0.19
At least comfortable (Aug–Oct 2020)	0.92	0.91
Urban household (Nov–Dec 2020)	0.33	0.46***
No longer lives in natal household (Nov–Dec 2020)	0.35	0.42*
Household size (Aug–Oct 2020)	3.92	3.73
New health expenses in 2021	0.24	0.27
Rise in food prices in 2021	0.37	0.33
Illness of income earner in 2021	0.03	0.04
Natural disaster in 2021	0.03	0.03
Fall in output prices in 2021	0.16	0.18
Number of individuals	803	159
Sample proportion (%)	83.5	16.5

Notes: Wealth terciles are based on the Young Lives Round 5 (2016) wealth index (Briones, 2017). The variables 'At least struggling' and 'At least comfortable' are derived from a subjective measure of household wealth based on a Likert scale, whereby a response of 1 represents 'destitute' and a response of 6 represents 'very rich'. 'At least struggling' takes the value of one if a participant answers 'destitute, 'poor' or 'struggling', while 'At least comfortable' takes the value of one if a participant answers 'comfortable', 'rich' or 'very rich'. Cantril (1965) self-anchoring scale asks the young people to visualize a ladder of nine steps, with the bottom step representing the worst life for them and the top step representing their best possible life. Respondents were asked to identify which step they presently stood on. The variable 'No longer lives in natal household' takes the value of one if there is no parent or aunt/uncle present in the household. Results of t-tests of the equality of means between those who maintained work in 2021 and those who lost their job in 2021 are reported. * denotes significance at 10 %, ** significance at 5 % and *** significance at 1 %.

Table 2
The relationship between job loss and mental health.

	Anxiety		Depression	
	GAD-7 score	*At least mild anxiety*	*PHQ-8 score*	*At least mild depression*
Lost work in 2021	0.581**	0.059**	0.287	0.013
	(0.235)	(0.028)	(0.231)	(0.028)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	2,871	2,871	2,869	2,869

Note: All specifications control for household location (urban/rural), household size, whether the household experienced new health expenses, inflation, natural disasters, illness and a fall in output prices, and individual and survey call fixed effects. Robust standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

often in response to chronic stress or adversity (Mazure, 1998).

Fig. 3 shows the changes over time in the proportion of individuals who report symptoms consistent with at least mild anxiety. An inspection of the changes in 2020 suggests that the trends appear parallel prior to the fourth COVID-19 wave. However, individuals who lost their jobs in 2021 experienced significantly larger increases in symptoms of anxiety. Among those who lost their job, the proportion with at least mild anxiety rose by 83% in 2021, from 6.9% to 12.7% (the difference between the proportion in November–December 2020; November–December 2021 is statistically significant at the 10% level). In contrast, there was no significant change among those who maintained work in 2021.

Having established that job loss during the fourth COVID-19 wave in Vietnam is associated with increases in young people's symptoms of anxiety, we next move on to identifying possible heterogeneity. Fig. 4 reports the heterogeneous associations between job loss and symptoms of anxiety according to young people's age, call 2 monthly earnings terciles, and whether the participant still lives in their natal household (full regression results are in Table A.2 in the Appendix).

We find that only an increase in anxiety for the Older Cohort (predicted at 10.9 ppts; 95% CI: 2.0, 19.8) is significantly different from zero, although there is no significant difference between this prediction and the prediction for the Younger Cohort (2.3 ppts; 95% CI: 4.3, 8.9). We also find that the increase in anxiety due to job loss is only significantly different from zero among the top earnings tercile (predicted at 16.2 ppts; 95% CI: 1.7, 30.7), and that there is a significant difference between the top and bottom earnings tercile (but not the middle tercile). Lastly, we find that the increase in anxiety is only significant among those no longer living in their natal household (estimated at 12.0 ppts; 95% CI: 2.8, 21.5), but not among those still living with their parents.

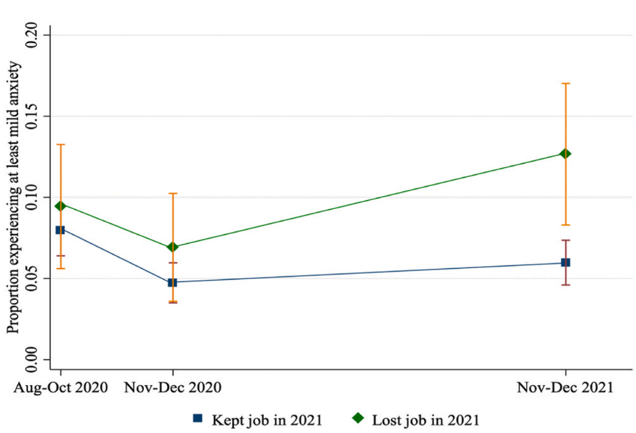

Fig. 3. Changes in anxiety over time.
Notes: Vertical bars indicate a 90% confidence interval around the mean.

This finding is in line with Alam and Bose (2022), who conclude that job loss among young adults in the U.S. only led to a deterioration of mental health when they were living independently, but not when they were still living with their parents.

When trying to understand the earnings results, we find evidence that, at least in part, the differences according to wealth are linked to differences in household composition. Nearly three-quarters of young adults in the lowest earnings tercile still live in their natal households, while only roughly half of the respondents in the top earnings tercile still live in their natal household (the difference in proportions between the bottom and top earnings terciles is significant at the 1% level). This is in line with existing literature which finds that migration rates out of the household in Vietnam are typically higher for well-educated individuals from higher-income households than the poor, who may lack the means to move (Coxhead et al., 2015).

Splitting the top earnings tercile sample by whether participants still live in their natal households, and estimating equation (1) separately, suggests that the result among the top tercile appears to be driven entirely by individuals who are no longer in their natal households; in the sample who still live in their natal households, the coefficient on job loss is no longer statistically significant (Table A.2 in the Appendix). However, we interpret these results with the caveat that only a small number of individuals lost their job in the highest earnings tercile (15% of the highest earnings tercile sample).

Finally, although Table 2 shows no significant association between job loss and symptoms of depression in the full sample, this average may mask significant associations within specific subgroups. To examine this, we assess heterogeneous associations between job loss and at least mild depression, following the same approach used for anxiety (results shown in Figure A.3 in the Appendix). Across all subgroups considered, we find no significant relationship between job loss and changes in the probability of experiencing at least mild depression.

3.3. *Sensitivity analyses*

Our results suggest a strong association between job loss and increased anxiety during the pandemic, but no corresponding evidence of an association with depression. However, there are many channels through which the pandemic may have affected mental health. Prior research indicates that individuals who were infected with COVID-19—or just perceived themselves at higher risk—were more likely to experience mental health conditions (Mazza et al., 2020; Porter et al., 2022). This implies that, if job losses were correlated with a higher prevalence of COVID-19 cases, our results may conflate other channels through which COVID-19 affects anxiety, rather than the effect of job losses per se.

To account for this, we include Google Trends information in each district, controlling for the prevalence of searches on the topic 'COVID-19 testing'. The assumption is that the number of Google searches on the topic 'COVID-19 testing' increases with the number of COVID cases. This seems to be the case: at the national level, Google search information on 'COVID-19 testing' is significantly correlated with daily confirmed COVID-19 cases (Pearson's correlation of 0.684, significant at the 1% level). We match each respondent's interview date to the closest available Google Trends data within a week and find that our results remain robust (Tables B.1–B.2 in the Appendix).

While the previous robustness check helps assuage concerns that the results are driven by general COVID-19 anxiety, it relies on Google search data, which inherently depends on the availability of digital devices and internet penetration. Consequently, if access to digital devices or internet coverage varies across regions, this approach may have limitations. Therefore, as an additional sensitivity check, we re-estimate our models controlling for cumulative national confirmed COVID-19 cases at the interview date (data retrieved from https://ourworldindata.org/covid-cases) and self-reported perceived infection risk (on a Likert scale ranging from 'no risk' to 'high risk'). Our findings remain

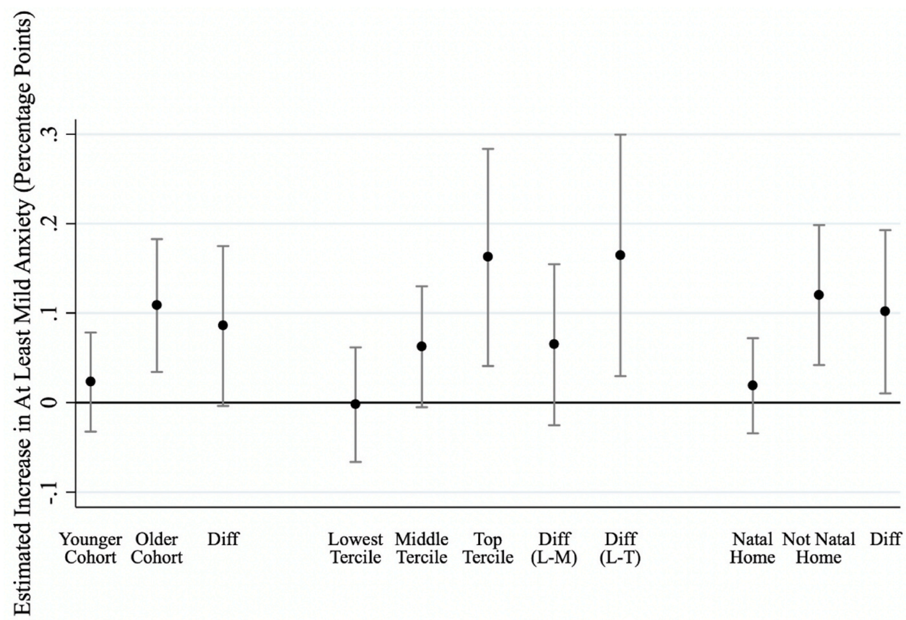

Fig. 4. Predicted increase in at least mild anxiety by sub-groups.
Notes: Predictions for each group are calculated using equation (2). (L–M) and (L–T) refer to the difference between the Lowest Tercile and the Middle Tercile, and the Lowest Tercile and the Top Tercile, respectively. All specifications control for household location (urban/rural), size, whether the household experienced new health expenses, inflation, natural disasters, illness and a fall in output prices, and individual and survey call fixed effects. Vertical bars indicate a 90% confidence interval around predictions.

consistent across both specifications (Tables B.3–B.6 in the Appendix), reinforcing the interpretation that job loss, rather than COVID-19 exposure, explains the observed rise in anxiety.

Beyond concerns about COVID-19 exposure, another potential source of bias arises from imbalances in key baseline characteristics between those who lost their jobs and those who maintained employment. As shown in Table 1, there are significant differences in age, gender, education, and income between the two groups, which could independently contribute to differences in mental health. To further test the robustness of our findings in Table 2, we apply entropy balancing to reweight the sample, ensuring that age, gender, years of education, health insurance status, monthly earnings, and urban location are balanced between the two groups. After implementing entropy balancing, our main results remain consistent with those in Table 2 (Table B.7 in the Appendix). This suggests that the observed relationship between job loss and anxiety is unlikely to be driven by these pre-existing differences in baseline characteristics.

Lastly, while entropy balancing addresses observed baseline differences between those who lost their jobs and those who maintained employment, another consideration is the broader representativeness of our sample. By design, the Young Lives households tend to be slightly poorer than those in nationally representative datasets. Additionally, attrition between the first survey in 2002 and the COVID-19 phone survey has resulted in an over representation of females and individuals in rural areas (Table C.1 in the Appendix). To address these demographic biases, we apply post-stratification weights for age, gender, urban/rural location, and region to re-weight the sample such that we match the nationally representative sample from the Population and Housing Census. Re-estimating our main results using these weights, we find that the interpretation of our findings remains unchanged (Tables C.2–C.3 in the Appendix).

3.4. Decomposition of channels underlying the increase in anxiety

Building on our main findings, which indicate a strong association between job loss and increased anxiety, we now turn to exploring potential mechanisms driving this relationship. To examine this, we estimate Equation (3), incorporating the potential mediating variables discussed in Section 2.3.

We present our estimates of Equation (3) in Table 3. In line with existing literature, we find that changes in food insecurity and household wealth significantly predict changes in anxiety. As expected, we also find that job loss during 2021 significantly predicts decreases in perceived household wealth and increases in mild food insecurity (results presented in Appendix D). Comparing the estimated coefficients of *Lost Job* in Table 3 ($\tilde{\beta}$) to those in Table 2 (β), we find that controlling for changes in food insecurity and household wealth reduces the effect of job loss on anxiety by 22.2% (GAD-7 score) and 18.6% (at least mild anxiety indicator). However, the coefficient of interest remains statistically significant (at the 10 % level) and economically meaningful. This suggests that, although financial strain may explain a non-trivial proportion of the increase in anxiety associated with job loss, the majority of this increase remains unaccounted for.

Table 3
The effect of job loss on anxiety controlling for changes in household wealth and food insecurity.

	GAD-7 score	At least mild anxiety
Lost work in 2021	0.452*	0.048*
	(0.233)	(0.028)
Mild food insecurity	0.375**	0.038*
	(0.168)	(0.022)
Struggling	1.152***	0.083**
	(0.304)	(0.033)
Controls	Yes	Yes
Observations	2,869	2,869

Note: All specifications control for household location (urban/rural), size, whether the household experienced new health expenses, inflation, natural disasters, illness and a fall in output prices, and individual and survey call fixed effects. Robust standard errors are reported in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

4. Discussion

Despite recurrent calls for investment into research and policies that target young adults during this critical stage of their lives (Stroud et al., 2015), there is a dearth of evidence on the consequences of job loss on mental health among this group. In this paper, we analyse the association between job loss during the fourth COVID-19 wave in Vietnam and levels of anxiety and depression among young adults. Our results indicate that experiencing job loss is associated with a significant increase in the levels of anxiety, but not depression. Specifically, we find that employment loss during the fourth COVID-19 wave is associated with a 5.9 percentage point increase in the probability of experiencing symptoms consistent with either mild or severe anxiety. This is driven by individuals in the top earnings tercile who no longer live in their natal household—suggesting that the association between job loss and anxiety is most acute among individuals who are likely primary earners in their household.

A direct comparison of our results with previous studies is complicated by differences in the measurement of mental health outcomes. Nonetheless, our findings indicate that the effect of job loss on mental health among young adults in Vietnam is substantial and, in some cases, larger than what has been documented in high-income country contexts. For instance, Alam and Bose (2022), studying young adults in the United States, report that job loss led to a 14% increase in a worry index, which captures feelings of discouragement about the future, concerns about not having a good job, and financial insecurity. In contrast, we find that job loss in Vietnam led to a 115% increase in the probability of experiencing at least mild anxiety. Similarly, comparing our results to fixed-effects estimates from Cygan-Rehm et al. (2017), who study job loss and mental health across multiple high-income countries, we find that our estimated 0.27 SD increase in anxiety symptoms is larger than estimates from Australia and Germany and is roughly equivalent to the estimate from the United States. However, it is lower than the estimated effect in the UK.

The broader implication of our findings is that the effects of job loss on mental health are likely shaped by a combination of economic security, cultural expectations, and institutional support. The stronger effects observed in Vietnam compared to some developed countries may reflect differences in social safety nets and financial security. At the same time, the fact that our estimates are lower than those reported for the UK suggests that economic insecurity alone does not fully explain the relationship between job loss and mental health, and that other non-pecuniary factors may also play a role. This is consistent with our decomposition findings, which indicates that up to 22% of the relationship between job loss and anxiety may be operating through changes in perceived household wealth and food insecurity. Aside from financial strain, literature suggests that loss of employment may engender profound non-pecuniary changes in the lives of working individuals—such as loss of valued relationships and perceived identity—which may have important detrimental effects on their mental health (Hetschko et al., 2014). Similarly, job loss may lead to a sense of loss of personal control over life outcomes, which may have adverse impacts on mental health (Price et al., 2002). Measures of such non-pecuniary considerations were not captured in the Young Lives phone surveys, which precludes us from including them in our analysis.

While the results presented here are, by definition, short-term, they may have important implications for public policy measures aimed at reducing mental health problems (Collins et al., 2011). This may be particularly true if the detrimental effects of job loss on anxiety persist and leave enduring scars that can be traced for many years, even after re-employment. These long-term scarring effects have been well-documented among individuals in high-income countries, particularly among young workers (e.g., Clark et al., 2001; Lucas et al., 2004).

The fact that a large portion of the negative relationship between job loss and anxiety is not explained by measured financial strain implies that policymakers are unlikely to fully remediate the effects with cash or food transfer programmes. While such interventions may mitigate economic distress, additional measures—such as community-based mental health support—may be particularly relevant in LMICs, where job loss likely carries both economic and social consequences. Providing mental health and psychosocial support for young people is therefore of critical importance, in addition to active policies aimed at helping young people re-enter the labour market and sustain employment. These interventions are especially important for young people facing financial pressure as primary earners in their households, as they may experience heightened mental health challenges following job loss.

CRediT authorship contribution statement

Richard Freund: Writing – original draft, Methodology, Formal analysis. **Marta Favara:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Catherine Porter:** Writing – review & editing, Methodology, Funding acquisition, Data curation, Conceptualization. **Douglas Scott:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Le Thuc Duc:** Writing – review & editing, Data curation.

Ethics approval

The Central University Research Ethics Committee of the University of Oxford provided ethical approval for the data collection underlying this paper (CUREC 1A/ODID CIA-20-034).

Funding

This work was supported by the United Kingdom aid from the Foreign, Commonwealth, and Development Office (Grant no. GB-GOV-1-301108). The funder had no role in the design, interpretation or write-up of the study, or in the decision to submit the study for consideration for publication.

Declarations of interest

None.

Acknowledgements

Many thanks to Alan Sánchez for useful comments and feedback.

Appendix A. Supplementary data

Supplementary data to this article can be found online at doi: mmcdoino

Data availability

The data that support the findings of this study are publicly available from the UK Data Archive.

References

Adams-Prassl, A., Boneva, T., Golin, M., Rauh, C., 2020. Inequality in the impact of the coronavirus shock: evidence from real time surveys. J. Publ. Econ. 189, 1–33.
Alam, S.A., Bose, B., 2022. Stepping into adulthood during a recession: did job losses during the Great Recession impact health of young adults? Health Econ. 31, 1730–1751.
Alloush, M., 2023. Income, Psychological Well-Being, and the Dynamics of Poverty. Economic Development and Cultural Change.
Baranov, V., Grosjean, P., Khan, F.J., Walker, S., 2022. The impact of COVID-related economic shocks on household mental health in Pakistan. Health Econ. 31 (10), 2208–2228.
Bartelink, V.H.M., Ya, K.Z., Guldbrandsson, K., Bremberg, S., 2020. Unemployment among young people and mental health: A systematic review. Scand. J. Publ. Health 48, 544–558.

Boland, R.J., Keller, M.B., 2009. Course and outcome of depression. In: Gotlib, I.H., Hammen, C.L. (Eds.), Handbook of Depression, second ed. Guilford, New York, NY, pp. 23–43.
Briones, K., 2017. How many rooms are there in your house? Constructing the young lives wealth index. Young Lives Technical Note 43, 1–18. Young Lives, Oxford.
Cantril, H., 1965. The Pattern of Human Concerns. Rutgers University Press, New Brunswick, NJ.
Charles, K.K., DeCicca, P., 2008. Local labor market fluctuations and health: is there a connection and for whom? J. Health Econ. 27 (6), 1532–1550.
Clark, A., Georgellis, Y., Sanfey, P., 2001. Scarring: the psychological impact of past unemployment. Economica 68 (270), 221–241.
Collier, K.M., Weiss, B., Pollack, A., Lam, T., 2020. Explanatory variables for women's increased risk for mental health problems in Vietnam. Soc. Psychiatr. Psychiatr. Epidemiol. 55, 359–369.
Collins, P.Y., Patel, V., Joestl, S.S., March, D., Insel, T.R., Daar, A.S., et al., 2011. Grand challenges in global mental health. Nature 475 (7354), 27–30.
Cochard, F., Le Gallo, J., Georgantzis, N., Tisserand, J.-C., 2021. Social preferences across different populations: meta-analyses on the ultimatum game and dictator game. J. Behav. Exp. Econ. 90, 101613.
Coxhead, I., Cuong, N.V., Vu, L.H., 2015. Migration in Vietnam: new evidence from recent surveys. In: Vietnam Development Economics Discussion Paper. World Bank Group, Washington, DC.
Cygan-Rehm, K., Kuehnle, D., Oberfichtner, M., 2017. Bounding the causal effect of unemployment on mental health: nonparametric evidence from four countries. Health Econ. 26, 1844–1861.
Engel, C., 2011. Dictator games: a meta study. Exp. Econ. 14, 583–610.
Fafchamps, M., 2011. Risk sharing between households. In: Pages 1255 1279 of: Handbook of Social Economics, vol. 1. Elsevier.
Fava, M., Rankin, M.A., Wright, E.C., Alpet, J.E., Nierenberg, A.A., Pava, J., et al., 2000. Anxiety disorders in major depression. Compr. Psychiatry 41, 97–102.
Favara, M., Crivello, G., Penny, M., Porter, C., Revathi, E., Sánchez, A., Scott, D., Duc, L. T., Woldehanna, T., McKay, A., 2021. Cohort profile update: the Young Lives study. Int. J. Epidemiol. 5 (6), 1784–1785.
Forsythe, E., 2022. Why don't firms hire young workers during recessions? Econ. J. 132 (645), 1765–1789.
Ganson, K.T., Tsai, A.C., Weiser, S.D., Benabou, S.E., Nagata, J.M., 2021. Job insecurity and symptoms of anxiety and depression among U.S. Young adults during COVID-19. J. Adolesc. Health 68, 53–56.
General Statistics Office, 2021. Report on the Covid-19 Impacts on Labour and Employment Situation in the Third Quarter of 2021. Ha Noi, Vietnam.
Guerin, R.J., Barile, J.P., Thompson, W.W., McKnight-Eily, L., Okun, A.H., 2021. Investigating the impact of job loss and decreased work hours on physical and mental health outcomes among US adults during the COVID-19 pandemic. J. Occup. Environ. Med. 63 (9), 571–579.
Guiso, L., Paiella, M., 2008. Risk aversion, wealth, and background risk. J. Eur. Econ. Assoc. 6 (6), 1109–1150.
Haushofer, J., 2019. Is there a Psychological Poverty Trap? Mimeo.
Hetschko, C., Knabe, A., Schöb, R., 2014. Changing identity: retiring from unemployment. Econ. J. 124 (575), 149–166.
Hossain, M., 2021. COVID-19 and gender differences in mental health in low- and middle-income countries: young working women are more vulnerable. Social Science and Medicine – Mental Health 1, 100039.
International Labour Organization, 2021a. World Employment and Social Outlook: Trends 2021. International Labour Office, Geneva. ISBN 978-92-2-031959-8.
International Labour Office, 2021b. World Social Protection Report 2020–22: Social Protection at the Crossroads – in Pursuit of a Better Future. ILO, Geneva.
Jones, A.D., 2017. Food insecurity and mental health status: a global analysis of 149 countries. Am. J. Prev. Med. 53 (2), 264–273.
Kerr, A., 2018. Job flows, worker flows and churning in South Africa. S. Afr. J. Econ. 86, 141–166.
Kroenke, K., Strine, T.W., Spitzer, R.L., et al., 2009. The PHQ-8 as a measure of current depression in the general population. J. Affect. Disord. 114, 163–173.
Le, M.T.H., Nguyen, H.T., Tran, T.D., Fisher, J.R.W., 2012. Experience of low mood and suicidal behaviors among adolescents in Vietnam: findings from two national population-based surveys. J. Adolesc. Health 51, 339–348.
Lucas, R.E., Clark, A.E., Georgellis, Y., Diener, E., 2004. Unemployment alters the set point for life satisfaction. Psychol. Sci. 15 (1), 8–13.
Marcus, J., 2013. The effect of unemployment on the mental health of spouses—evidence from plant closures in Germany. J. Health Econ. 32 (3), 546–558.
Mazure, C.M., 1998. Life stressors as risk factors in depression. Clin. Psychol. Sci. Pract. 5, 291–313.
Mazza, M.G., De Lorenzo, R., Conte, C., et al., 2020. Anxiety and depression in COVID-19 survivors: role of inflammatory and clinical predictors. Brain Behav. Immun. 89, 594–600.
McInerney, M., Mellor, J.M., Nicholas, L.H., 2013. Recession depression: mental health effects of the 2008 stock market crash. J. Health Econ. 32, 1090–1104.
Nguyen, A., 2003. Cultural and Social Attitudes towards Mental Illness in Ho Chi Minh City, vol. 2. Seattle University Research Journal, Vietnam, pp. 27–31.
Nguyen, N.P., 2008. An assessment of the young lives sampling approach in Vietnam. In: Young Lives Technical Note. Young Lives, Oxford.
Nguyen, T.Q., Bandeen-Roche, K., Bass, J.K., German, D., Nguyen, N.T.T., Knowlton, J., 2016. A tool for sexual minority mental health research: the patient health questionnaire (PHQ-9) as a depressive symptom severity measure for sexual minority women in Viet Nam. J. Gay Lesb. Ment. Health 20, 173–191.
Novo, M., Hammarström, A., Janlert, U., 2001. Do high levels of unemployment influence the health of those who are not unemployed? A gendered comparison of young men and women during boom and recession. Soc. Sci. Med. 53 (3), 293–303.
Paul, K.I., Moser, K., 2009. Unemployment impairs mental health: meta-analyses. J. Vocat. Behav. 74, 264–282.
Peng, L., Meyerhoefer, C.D., Zuvekas, S.H., 2013. The Effect of Depression on Labor Market Outcomes. NBER Working Paper Series. Working Paper 19451.
Pham Tien, N., Pham Thanh, T., Nguyen Hanh, D., et al., 2021. Utilization of mental health services among university students in Vietnam. Int. J. Ment. Health 50 (2), 113–135.
Porter, C., Favara, M., Hittmeyer, A., Scott, D., Sánchez, A., Ellanki, R., Woldehanna, T., Duc, L.T., Craske, M.G., Stein, A., 2021. Impact of the COVID-19 pandemic on anxiety and depression symptoms of young people in the global south: evidence from a four-country cohort study. BMJ Open.
Porter, C., Hittmeyer, A., Favara, M., Scott, D., Sánchez, A., 2022. The evolution of young people's mental health during COVID-19 and the role of food insecurity: evidence from a four low-and-middle-income-country cohort study. Pub. Health Pract. 3, 100232.
Posel, D., Oyenubi, A., Kollamparambil, U., 2021. Job loss and mental health during the COVID-19 lockdown: evidence from South Africa. PLoS One 16 (3), e0249352.
Price, R.H., Choi, J.N., Vinokur, A.D., 2002. Links in the chain of adversity following job loss: how financial strain and loss of personal control lead to depression, impaired functioning, and poor health. J. Occup. Health Psychol. 7 (4), 302–312.
Ridley, M., Rao, G., Schilbach, F., Patel, V., 2020. Poverty, depression, and anxiety: causal evidence and mechanisms. Science 370, 1–12.
Sawyer, S.M., Azzopardi, P.S., Wickremarathne, D., Patton, C., 2018. The age of adolescence. Lancet Child and Adolescent Health 2, 223–228.
Scott, D., Freund, R., Favara, M., Porter, C., Sánchez, A., 2021. Unpacking the Post-lockdown Employment Recovery of Young Women in the Global South. IZA Discussion Paper Series, No. 14829.
Spitzer, R.L., Kroenke, K., Williams, J.B.W., Löwe, B., 2006. A brief measure for assessing generalized anxiety disorder: the GAD-7. Arch. Intern. Med. 166, 1092–1097.
Stroud, C., Walker, L.R., Davis, M., Irwin, C.E., 2015. Investing in the health and well-being of young adults. J. Adolesc. Health 56 (2), 127–129.
von Wachter, T., Bender, S., 2006. In the right place at the wrong time: the role of firms and luck in young workers' careers. Am. Econ. Rev. 96 (5), 1679–1705.
Vuong, D.A., Ginneken, E.V., Morris, J., Ha, S.T., Busse, R., 2011. Mental health in Vietnam: burden of disease and availability of services. Asian J. Psychiatry 4, 65–70.
Warr, P., 1987. Work, Unemployment and Mental Health. Clarendon Press, Oxford.
Witteveen, D., Velthorst, E., 2020. Economic hardship and mental health complaints during COVID-19. Proc. Natl. Acad. Sci. USA 117 (44), 27277–27284.
Zhong, Q-Yl, Gelaye, B., Zaslavsky, A.M., Fann, J.R., Rondon, M.B., Sánchez, S.E., Williams, M.A., 2015. Diagnostic validity of the generalized anxiety disorder - 7 (GAD-7) among pregnant women. PLoS One 10, e0125096.