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Do Refugees with Better Mental Health Better Integrate?
Evidence from the *Building a New Life in Australia* Longitudinal Survey

Hai-Anh H. Dang, Trong-Anh Trinh and Paolo Verme*

Abstract
Hardly any evidence exists on the effects of mental illness on refugee labor outcomes. We offer the first study on this topic in the context of Australia, one of the host countries with the largest number of refugees per capita in the world. Analyzing the *Building a New Life in Australia* longitudinal survey, we exploit the variations in traumatic experiences of refugees interacted with post-resettlement time periods to causally identify the impacts of refugee mental health. We find that worse mental health, as measured by a one-standard-deviation increase in the Kessler mental health score, reduces the probability of employment by 14.1% and labor income by 26.8%. We also find some evidence of adverse impacts of refugees' mental illness on their children's mental health and education performance. These effects appear more pronounced for refugees that newly arrive or are without social networks, but they may be ameliorated with government support.

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Key words: refugees, mental health, labor outcomes, instrumental variable, BNLA longitudinal survey, Australia

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1. Introduction

The number of forcibly displaced persons worldwide has more than doubled over the past three decades, reaching 84 million (or more than 1% of the world population) by the middle of 2021. About 15% of this figure is hosted by European countries, with Turkey and Germany being among the largest refugee-hosting countries over the world.[1] One thorny issue faced by host countries, richer and poorer alike, is the low employment rate of refugees compared with those of citizens and other immigrants (Dustmann et al., 2017), a phenomenon that can persist even in the long run (Brell et al., 2020). Lack of refugee integration not only generates substantial financial costs for the host country but can lead to other social issues such as increased crime levels and reduced schooling outcomes of children in the host population (Piopiunik and Ruhose, 2017; Di Maio and Nisticò, 2019). As such, policies that improve the labor market outcomes of refugees can lead to increased returns for both refugees and their hosts.

Poor mental health has been shown to have detrimental impact on labor market outcomes (e.g., Chatterji et al., 2011). Since mental health is an important component of an individual's stock of human capital, mental illness may impair individuals' ability to obtain employment and maintain their earnings, by affecting factors such as productivity, motivation, and social relationships (Heckman et al., 2006; Cunha and Heckman, 2007). Having experienced conflicts and persecution first-hand, refugees are especially vulnerable to mental health issues. Indeed, more than one-fifth of refugees are estimated to suffer from anxiety, depression, or post-traumatic stress disorder (PTSD), and forced migrants could be 10 times more likely to have mental health issues compared to the local population (Fazel et al., 2012; Bogic et al., 2015; Moya, 2018).

We provide the first study to examine the relationship between mental health and refugees' labor market outcomes. We use Australia as a uniquely interesting case study. The country has

[1] https://www.unhcr.org/figures-at-a-glance.html and UNHCR (2021).

a long tradition of resettling humanitarian migrants through its Humanitarian Programme—which is the world's second largest resettlement program managed in collaboration with the United Nations High Commissioner for Refugees (UNHCR) (behind only the United States). However, the living conditions of humanitarian migrants are not comparable to the general population. In particular, the refugee employment rate is around 23%, with a gap of up to 55 percentage points compared to the citizens' employment rate. This gap is around half and five times higher than the corresponding figures for the U.K. and the U.S., respectively (Brell et al., 2020). Australia is also the only country that mandates immigration detention for all "unlawful" arrivals, including those seeking protection as refugees. Therefore, understanding the effect of mental health on refugee labor outcomes is vital for designing refugee policies not only in Australia but also in other richer countries facing a large influx of refugees.

We analyze rich data on refugees from the *Building a New Life in Australia* (BNLA) longitudinal survey, which is also the largest survey of humanitarian migrants in Australia.[2] We investigate the causal impact of mental illness on labor market outcomes for refugees, employing an instrumental variable model with individual fixed effects that allows us to address various econometric issues such as endogeneity and reverse causality (i.e., while a mentally healthier refugee is more likely to be employed, being unemployed may deteriorate their mental health status). We instrument for mental health with the interaction term between past trauma exposure and a year dummy variable indicating the time period after arrival. This choice of instrument is motivated by insights from a large number of studies in the epidemiological literature that show a strong relationship between pre-displacement trauma and post-displacement mental health (Fazel et al., 2012) and that trauma-related mental illness tends to diminish over time (Steel et al., 2002; Moya, 2018).

[2] We use the term humanitarian migrants and refugees interchangeably in this paper given most respondents of the BNLA survey are refugees (more than 70%).

We find that worse mental health, as measured by a one standard deviation increase in the Kessler Psychological Distress Scale, decreases the probability of employment (conditional on being in the labor force) by 14.1% (6.4 percentage points), and weekly labor income by 26.8% ($192 Australian dollars). We also find that refugees with worse mental health are more likely to be out of the labor force or to work in lower-quality jobs (e.g., jobs with low skills level or in agriculture), and are less satisfied with their life. There is some evidence of negative externalities on their family members regarding their partners' life satisfaction and their children's mental health status and school performance. But these effects appear stronger for newly arrived refugees and less pronounced for those who have stronger social networks or receive benefits from the government.

Our study advances the existing literature in several ways. We first add to a sizeable empirical literature that examines the adverse labor outcomes caused by worse mental health (e.g., Kessler et al., 1999; Chatterji et al., 2011; Frijters et al., 2014). We depart from this literature by focusing on refugees, a unique population that are more susceptible to mental health disorders. Furthermore, since the refugees are at a disadvantage in the labor market as earlier discussed, the potentially negative effects of mental health may be quite different for them.

By focusing on refugees, we also contribute to the literature on their economic integration in host countries.[3] Previous research has identified a number of important factors that influence refugee integration, such as proficiency in the language of the receiving country (e.g., Clausen et al., 2009; Lochmann et al., 2019), and social networks (e.g., Beaman, 2012; Dagnelie et al., 2019; Villalonga-Olives et al., 2022). Yet, to our knowledge, no study investigates the causal impact of mental health on labor market outcomes of refugees.[4] Incidentally, we also contribute

[3] See Brell et al. (2020) and Verme and Schuettler (2021) for recent reviews of the impact of forced migration on host communities.

[4] Some studies casually examine the relationship between refugee mental health and their labor market outcomes. For example, Connor (2010) finds no correlation between reporting sadness/depression and employment

to the small literature on the outcomes of refugees' children, which is constrained by data limitations (e.g., Åslund et al., 2011; Adelman, 2013).

Finally, our findings add to a broader literature that examines how policy interventions affect immigrants' labor market outcomes. For instance, LoPalo (2019) shows that receiving welfare benefits has no significant effects on refugee employment in the United States, although it leads to an increase in their wages in the long run. Similarly, studying the labor market effects of granting job permits to undocumented Venezuelan migrants in Colombia, Bahar et al. (2021) find little impacts on hours worked, wages, and labor force in the short to medium run. Agersnap et al. (2020) find that welfare generosity can attract migrants and estimate the elasticity of migration with respect to benefits to be 1.3. On the other hand, Arendt et al. (2021) show that reform on improving Danish language training could have positive effects on refugees' employment and earnings, improve the secondary school completion rate, and reduce the probability of crime for their male children. By examining the little explored relationship between mental health and labor market outcomes of refugees, our paper offers valuable insights for health and labor policies, in Australia and elsewhere, that aim at better integrating refugees into host countries.

This paper consists of six sections. We provide an overview of refugees' policies in Australia in Section 2. We subsequently describe the database that we construct for analysis in Section 3 before discussing the empirical model in Section 4. In Section 5, we present the main findings (Section 5.1) together with robustness checks (Section 5.2), and heterogeneity analysis (Section 5.3). We finally conclude in Section 6.

2. Country background

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outcomes in the United States. Ruiz and Vargas-Silva (2018) show that refugees are 2.8 percentage points more likely to report a mental health problem in the United Kingdom, which may be one of the contributing factors for their worse labor market outcomes compared to citizens and other migrants.

Australia is one of 22 UNHCR resettlement countries that provides physical and legal protection for those living in perilous situations or have specific needs that cannot be addressed in the country of origin and will allow for them to become naturalized citizens. The country has a long tradition of resettling humanitarian migrants through its Humanitarian Programme—the world's second largest resettlement program with the UNHCR (behind only the United States)—and Australia hosts the largest number of refugees per capita in the world (Kenny, 2015). Australia had resettled more than 880,000 people through its Humanitarian Program between 1947 and 2019 (Shergold et al., 2019). The program classifies those who seek resettlement in Australia into three categories: (i) refugees (those who meet the UNHCR definition of a refugee); (ii) special humanitarians (those who do not precisely fit the UNHCR standard but are still under threat of persecution and have family in Australia); and (iii) asylum seekers (those who arrive in Australia and subsequently are granted refugee status).[5]

Over the past few decades, Australia's two leading political parties, the Liberal-National coalition and the Labor parties, have supported increasingly severe deterrence measures in an attempt to stem the flow of asylum seekers. Consequently, the share of recognized refugees is relatively low (around 3%) compared to the overall migrant intake (Phillips and Simon-Davies, 2016), and Australia is far behind other Western countries in terms of number of persons resettled (UNHCR, 2017). Figure A1 (Appendix A) shows that the number of people seeking asylum has increased over time; however, the number of those granted protection visas (granted refugee status) has declined during the same period.

Refugees in Australia are particularly vulnerable to poor mental health outcomes with the prevalence of mental disorders far exceeding those in the general population (Slewa-Younan et al., 2019). This is explained by a number of factors including past trauma

[5] From 2015, asylum seekers who arrive illegally without a valid visa are detained. For more details of the Australia Humanitarian Program, see Flatau et al. (2015).

experience, financial constraints, and other barriers to accessing health services such as language barriers, unfamiliarity of health services and perceived discrimination (Murray and Skull, 2005; Spike et al., 2011; Colucci et al., 2015). Australia was also the first Western country to implement mandatory detention provisions that required the detention of non-citizens who arrived without a valid visa. Evidence has shown that such mandatory detention is detrimental to mental health at all ages, in the short and long term (Steel et al., 2011). While screening for trauma and mental health conditions is mandated in Australian refugee health assessment guidelines for both refugees and asylum seekers, the validity of mental health screening in refugee groups has been questioned. As a result, rates of professional help-seeking among refugee groups are well below that of the non-refugee host population (Correa-Velez et al., 2007).

Regarding policies targeted at refugee employment, the Australian government has implemented a range of initial settlement services including accommodation assistance, language classes, and grant-based funding for projects to promote social cohesion and integration of refugees. Policies on employment for refugees, however, remain relatively poor (Shergold et al., 2019). An exception is the federal government program Jobactive, which is designed to connect job seekers with employers through a network of providers across the country.[6] Under the program, the Department of Human Services refers and assesses job seekers who receive benefits and are obliged to apply for jobs and undertake training. However, some evidence suggests that the program has failed to support refugees. A key challenge is the lack of specialist employment providers with expertise to support people from culturally and linguistically diverse backgrounds (Tahiri, 2017).[7] Consequently, refugees experience greater socio-economic disadvantage than other migrants, particularly in the labor market.

[6] There are also other initiatives implemented at the local level, such as the Refugee Employment Support Program in New South Wales and the Jobs Victoria Employment Network.
[7] Some other refugee employment programs such as *Career Pathways Pilot* (for newly arrived humanitarian refugees) and *Youth Transition Support* (for young people) have been shown to be ineffective in terms of

3. Data

The data used in this analysis are taken from the *Building a New Life in Australia* (BNLA), which is designed to trace the settlement journey of humanitarian migrants from their early months in Australia to their eligibility for citizenship. This is the largest survey of humanitarian migrants in Australia, and one of the largest studies of its type in the world (Edwards et al., 2018).[8] The first wave of data collection was undertaken between October 2013 and March 2014, and additional waves have been conducted annually using face-to-face interviews (in waves 1, 3 and 5) and telephone interviews (in waves 2 and 4). To be eligible for the study, participants had to have arrived in Australia in the three to six months preceding the start of wave 1 fieldwork and already be holding a permanent protection visa (the 'offshore' group), or to have been granted a permanent protection visa in the previous three to six months after their arrival in Australia by boat or on another visa type (the 'onshore' group). A total of 1,509 Principal Applicants, 755 adult Secondary Applicants and 135 adolescent Secondary Applicants (aged 15 to 17 years) were recruited to wave 1, yielding 2,399 participants in total. Figure A2 (Appendix A) shows that refugees in the BNLA survey came from 16 countries with the highest share from Iraq (40%), followed by Afghanistan (26%), and the Islamic Republic of Iran (12%). The attrition rate in BNLA is relatively lower than that in other surveys in Australia (Flatau et al., 2015). Among wave 1, 2,009 respondents (84%) were re-interviewed in wave 2, 1,894 (79%) in wave 3; 1,929 (80%) in wave 4, and 1,881 (78%) in wave 5.

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participation rates and outcomes achieved. For example, the number of clients enrolled in the *Career Pathways Pilot* program was 65% of the expected amount, and only 11% to 17% of participants having found employment in the same job as their pre-arrival occupation (Deloitte, 2019). In fact, many refugees find themselves unable to obtain this assistance and continue to rely on family and friends for employment opportunities (Shergold et al., 2019).

[8] Most studies examining labor market outcomes in Australia use a small sample of refugees. For example, Correa-Velez et al. (2015) use a sample of 233 refugees and find that length of time in Australia and informal networks, among others, were significant predictors of employment. Focusing on refugees living in Sydney, Waxman (2001) shows that those who had pre-immigration paid job experience, completed study/job training and better job searching knowledge/language skills are more likely to participate in the labor force. Newman et al. (2018) find correlation between social support and psychological well-being using a sample of 190 refugees in Melbourne.

A unique feature of this study is that it covers a wide range of topics including housing, English language proficiency, employment, financial circumstances, immigration experience and experiences of trauma and health, with additional information collected about children's settlement experiences at wave 3. In terms of labor market outcomes, the survey provides rich information on current employment status and employment characteristics, experience of unemployment and income and government benefits received, among others. Following the existing literature (e.g., Beaman, 2012; LoPalo, 2019), we use two measures of labor market outcomes available from the BNLA: (i) employment status conditional on being in the labor force (equal to one if having a paid job in the last seven days; and zero if not); and (ii) weekly labor income (measured by total real income of all jobs). In the additional analysis, we also examine other outcomes such as refugees' own labor market outcomes (including labor force participation (LFP), employment type, and employment skills levels and sector) and life satisfaction outcomes as well as their partners' and children's outcomes (including partner's employment status, child mental health, and school performance).

Information on health status of refugees includes self-rated health, injury or disability, life stressors and coping, and mental health. Our analysis focuses on the mental health of refugees measured by the six-item Kessler Screening Scale for Psychological Distress (K6). The K6 was developed by Kessler et al. (2002) and has been used widely in the economic literature for measuring non-specific psychological distress (e.g., Andersen, 2015; Gong et al., 2020). The six items ask individuals how often, during the past four weeks preceding the survey, an individual felt: (1) nervous, (2) hopeless, (3) restless or fidgety, (4) so depressed that nothing could cheer me up, (5) everything was an effort, and (6) life is meaningless (worthless). Respondents can choose among the following: all the time, most of the time, some of the time, little of the time, or none of the time. The answers are then scored on a five-point scale, with total scores ranging from 6 to 30, and a higher score indicating worse mental health.

For easier interpretation, we follow the common practice in the literature by standardizing mental health scores, such that the total score has a mean of zero and a standard deviation of one (e.g., Frijters et al., 2014).

Respondents in the BNLA survey were also asked about whether they had experienced or witnessed any traumatic events before arriving in Australia. These include extreme living conditions (e.g., lack of food, water, shelter or medicine), war/conflict, violence, kidnapping or imprisonment, political/religious persecution, natural disaster, and/or other events. We then create an indicator of any trauma experience, interacted with the time indicator, as the instrumental variable in our analysis. We also examine the intensity of trauma experience (measured by total events experienced by refugees) as a robustness check. For the heterogeneity analysis, we obtain information on a wide range of refugee characteristics before and after resettlement such as time spent in refugee camps, social networks, and local/government benefits received. We also supplement our analysis with data from the Household, Income and Labour Dynamics in Australia (HILDA) survey over the past two decades (2001 – 2019). Table 1 provides summary statistics of all the variables used in our analysis.

4. Empirical strategy

To investigate the relationship between refugee mental illness and their labor market outcomes, we estimate the following regression

$$Y_{it} = \beta MI_{it} + \gamma X_{it} + \mu_i + \tau_t + \epsilon_{it} \tag{1}$$

where Y_{it} are labor market outcomes of refugee *i* who was interviewed in wave *t*. We focus on two main outcome variables: employment status and weekly labor income (real income in \$1,000 Australian dollars). But we also examine other outcomes such as refugees' LFP, employment type, employment skills levels and sector, life satisfaction and their partners' and children's outcomes (including their partners' employment status and life satisfaction and their children's mental health and school performance).

The coefficient of interest in Equation (1) is β, which measures the impacts of mental illness (MI_{it}) on labor market outcomes. We also control for a range of (potentially) time-varying refugee characteristics in vector X_{it} including age groups, marital status, household size, language skills (listening, speaking, reading, and writing), home ownership, and residence areas (i.e., living in major cities versus remote areas).[9] These are important determinants of economic integration of refugees that have been examined in the literature (e.g., Lochmann et al., 2019; LoPalo, 2019).

We include the individual fixed effects (μ_i) to control for unobserved time-invariant characteristics at the individual level and the survey wave fixed effects (τ_t) to absorb the effects of unobservable time-varying characteristics that can commonly affect all refugees in each time period. ϵ_{it} is the error term. For continuous outcome variables, we estimate Equation (1) with the linear individual fixed effects model (FE). For outcome variables that are binary (i.e., yes/no variable) such as employment status, we estimate the logit individual fixed effects model (Logit-FE). We provide estimates with robust standard errors that are clustered at the individual level.

The attribution of causality to our findings requires the assumption that mental health issues are exogenous to labor market outcomes. However, there can be unobservable factors that are jointly correlated with mental illness and labor market outcomes, such as (time-varying) personality traits and innate family health background that can bias estimates. While the individual FE model can capture unobserved time-invariant factors (e.g., an individual might be born with some congenital mental health problem unobserved to the analyst that could

[9] We follow previous studies and use a set of dummies for the age variable to account for its nonlinear relationship with employment (e.g., Staubli and Zweimüller, 2013; Laun, 2017).

interfere with her job performance), it does not capture unobserved time-varying factors (e.g., this mental health problem could become worse or improve for different individuals over time). Furthermore, reverse causality remains another issue since unemployment might negatively affect an individual's mental health status (e.g., Currie et al., 2015; Frasquilho et al., 2016).[10] Specifically, if these unobservable factors are positively correlated with the labor outcomes, a naïve non-instrumented estimator of Equation (1) could lead to estimates that are upward biased toward zero (i.e., no impacts of mental health).

To causally identify the impacts of mental illness on refugee labor outcomes, we estimate Equation (1) using an instrumental variable (IV) model. We employ as our IV the interaction term between a dummy variable indicating refugees' exposure to any traumatic events before arriving in Australia and a variable indicating the time period after arrival (i.e., the years 2013 – 2018). Our first stage regression is as follows

$$MI_{it} = \alpha(TE_i \times t) + \eta X_{it} + \mu_i + \tau_t + \nu_{it} \qquad (2)$$

where TE_i is a binary variable indicating whether individual i was exposed to any traumatic events before resettlement, and t is the year indicator. As in Equation (1), we include individual and survey year fixed effects. We simultaneously estimate Equations (1) and (2) using the fixed effects IV logistic regression (IV-Logit-FE) for employment status and the fixed effects IV linear regression (IV-FE) for labor income.[11] Both models allow us to address reverse causality and unobserved individual heterogeneity concerns.

We now discuss the validity of the IV. A good instrumental variable should meet three conditions in our context: (i) exogeneity to the dependent variables (exogeneity condition); (ii) strong correlation with refugee's mental health (relevance condition); and (iii) affecting labor

[10] Given a large existing literature on the negative impacts of unemployment on mental health, we do not further investigate this relationship in this paper. We focus on the impacts of mental health on refugee labor outcomes since little evidence exists on this relationship.
[11] We estimate the fixed effects IV logistic regressions using the general simultaneous equation models (gsem) in Stata (Stata, 2019).

market outcomes only through changes in mental health status over time after resettlement (exclusion restriction condition).

The exogeneity condition is satisfied since the traumatic experiences experienced by refugees are typically caused by unexpected events such as war, conflict, or natural disasters. In fact, a number of economic studies have employed such exogenous events as IVs to identify causal impacts on health and education (e.g., Alderman et al., 2006; Di Maio and Nisticò, 2019). While a theoretically possible concern is that local market conditions in the host country may be among the determinants of conflict in the home country of the refugee, this concern is unlikely to be valid in practice. The roots of violent conflicts in the origin countries often come from endemic social/economic inequalities between groups in these countries themselves (Esteban et al., 2012; McGuirk and Burke, 2020).

Regarding the relevance condition, our IV is constructed based on evidence from the epidemiological literature showing that refugees are mostly exposed to stressful and potentially life-threatening situations before resettlement, and that pre-migration traumatic experiences are the most consistent factors associated with poor mental health (Bogic et al., 2015; Jankovic-Rankovic et al., 2020).[12] This is further supported by recent evidence from the economic literature that early-life exposure to war has a persistent effect on mental health (Singhal, 2019), but the impact may fade out with time (Moya, 2018).

The following simple example can help illustrate the rationale behind our identifying assumption. Consider a refugee living in Australia who was exposed to war/conflict in his home country. A possible IV may be a time-variant indicator representing the refugee's past exposure to these traumatic experiences. Indeed, plotting the OLS estimates of the impacts of traumatic experiences on standardized mental health scores and their 95% CIs (controlling for

[12] Studies in Australia have documented that traumatic experience of refugees leads to an increased risk of experiencing psychological trauma, including major depression, chronic anxiety, and PTSD (e.g., Steel et al., 2002; O'Donnell et al., 2020).

other variables), Figure 1 generally shows a strong correlation between refugees' exposure to traumatic events and mental illness. Specifically, we find that while the correlation between mental illness and certain specific events (such as physical or sexual violence, imprisonment or kidnapping, and political or religious persecution) is not statistically significant, it is strongly statistically significant and positive for most traumatic events such as lack of food, water, shelter, or medicine, war or other conflict, natural disasters (e.g., floods or drought), and/or other events. Overall, there is a strong correlation between refugees' exposure to *any* of these traumatic events and mental illness (as shown by the 95% CI at the bottom of Figure 1).

However, we argue that such instrument does not fully take into account the fact that refugees' traumatic experiences are time-varying. That is, these traumatic experiences may decline over the course of resettlement (Steel et al., 2002). Our IV improves on this instrument by exploiting both the differences of traumatic experience across refugees and its variation over time after the refugee settles in the host country. This strategy is, in fact, consistent with the spirit of other IVs recently employed in the literature such as the interaction between variations in time-varying oil prices and a country's distance to its nearest oil-producing countries, or the interaction between a donor's total time-varying annual aid budget with the recipient-specific probability of receiving aid from that donor (Nunn and Qian, 2014; Asatryan et al., 2017; Dreher et al., 2019; Dreher et al., 2021). Our subsequent formal statistical tests and robustness checks, discussed in the next section, further confirm the strength of the instrumental variable.

Regarding the exclusion restriction, one concern is that the IV can also affect labor market outcomes via other (unobserved) channels rather than just mental health. These can include, for example, physical health, past experience or other unobserved person-specific endurance over hardships. We take a multi-pronged approach to addressing these potential concerns. First, by employing the individual FE model, we only exploit within-refugee variations over time and eliminate all potentially confounding factors that are time-invariant. Second, we control for various time-varying refugee characteristics in the regressions such as age groups, marital status, household size, language skills, home ownership, and residence areas. We further offer robustness checks using physical and overall health or mental health in the previous period.

Finally, we conduct various stress tests on the IV, such as using a variant of the IV that involves summing up the total number of traumatic events experienced by refugees rather than just examining refugee exposure to these traumatic events. We also relax the exclusion restriction and provide upper bound and lower bound estimates as suggested by Conley et al. (2012). This helps gauge how large the direct effects of the IV on labor market outcomes (i.e., deviations from the exclusion restriction) would have to be to render the second stage results insignificant. Furthermore, we report different test statistics on the IV, including the Kleibergen-Paap F-statistics and the Anderson-Rubin confidence intervals (AR CI) to evaluate the strength of the IV (Dufour and Taamouti, 2005; Cameron and Miller, 2015).

5. Results

5.1. Main findings

As a first step, we employ a non-instrumented fixed-effects model and regress the two main labor market outcomes—employment status and weekly labor income—on mental health, conditioning on covariates as well as survey wave fixed effects. As discussed earlier, we standardize the mental health scores such that the mean and standard deviation equal zero and one, with higher scores indicating worse mental health. The estimation results are shown in Columns (1) and (3) in Table 2, with the full regression results shown in Appendix A, Table A1.[13] We present the estimates of the Logit-FE and IV-Logit-FE models as marginal effects, with the estimated coefficients provided in Table A2 (Appendix A). Column (1) demonstrates

[13] We also report in Table 2 the adjusted *p*-values for multiple hypothesis testing, as implemented in Newson (2010). The results reveal that the inference is not altered.

a negative correlation between having a paid job (conditional on being in the labor force) and mental illness. Similarly, poor mental health is also associated with lower labor incomes (Column (3)).

We turn next to the first stage regression results for the IV-Logit-FE and IV-FE models shown in the lower panel of Table 2. The IV has a negative and statistically significant effect on mental health. In other words, those who experienced trauma have worse mental health than those who did not, but the effects diminish over the course of resettlement. In particular, the Kleibergen-Paap F-statistics are between 17–19, which are larger than the benchmark value of 16.4 suggested by Stock and Yogo (2005). The 95% AR CIs confidence intervals lie entirely to the left of zero, further confirming that the IV is not a weak instrument and does not bias the estimates.

Columns (2) and (4) of Table 2 show the estimated effects of mental illness on labor market outcomes using our IV specification. We find that a one standard deviation increase in Kessler scores (worse mental health) decreases the probability of being employed by 6.4 percentage points (or 14.1%, which equals 6.4/45.4); it also decreases weekly labor income by $192 Australian dollars (or 26.8%).[14] These effects are highly statistically significant at the 1% level, and the IV-Logit-FE and IV-FE estimates are between 1.4 and 3.8 times larger than the FE estimates.[15]

While we offer the first estimates of the impacts of mental illness on refugees' labor outcomes, it can be useful to compare our estimated effects with those on the general population in previous studies. For example, analyzing data from the HILDA, Frijters et al. (2014) show that a one standard deviation decrease in mental health leads to a 30 percentage

[14] Our findings remain consistent when using the inverse hyperbolic sine transformation of the weekly labor income outcome (see Table A18, Appendix A).
[15] Our results differ from Connor (2010), who employs an non-instrumented approach and finds little evidence for the correlation between self-reported sadness/depression and earning among refugees in the United States. But the bias of the non-instrumented FE estimates that we find may partially contribute to this difference.

point decrease in the probability of being employed.[16] Using data from the National Comorbidity Survey-Replication (NCS-R) in the United States, Chatterji et al. (2011) find that psychiatric disorder is associated with reductions of 13-14 percentage points in the likelihood of employment. Findings from our study add new and useful evidence for policies to support refugees, who are especially vulnerable to mental illness as discussed earlier. We return to further comparison in Section 5.3.

Table 3 shows that mental illness also has a negative impact on other labor market outcomes.[17] Several findings stand out from this table. First, refugees with higher mental health scores are 3.5 percentage points (or 8.4%) less likely to participate in the labor force (Column (1)). Second, refugees with worse mental health are less likely to have a permanent job, although the effect is statistically insignificant (Column 2). They are also 3.2 and 5.6 percentage points (23.7% and 7.5%) more likely to work in low-skilled occupation and the agricultural sector (Columns (3)–(4)). Finally, worse mental health reduces the number of work hours by 10.1 (30.9%) and life satisfaction by 0.6 points (7.9%) on a 0-to-10 scale (Columns (5)–(6)). This is perhaps unsurprising given that mental health and life satisfaction are closely related (Danzer and Danzer, 2016). Our estimation results are thus consistent with the negative impacts of worse mental health on the probability of being employed and labor income discussed earlier (Table 2).

Once we establish strong evidence of the impacts of mental illness on refugees' labor market outcomes, we shift our attention to its spill-over effects on their family members. Table 4 shows that higher mental health scores lead to a lower probability of refugee partners being employed, although the coefficient is statistically insignificant (Column (1)). Mental illness

[16] The foreign-born population, however, is underrepresented in the HILDA survey (Watson and Wooden, 2010). Furthermore, it is not possible to identify refugees from HILDA as information on visa type is unavailable.
[17] We use the same IV approach as in Table 2 to examine other labor market outcomes. This requires an assumption that the exclusion restriction remains valid, or our instrument affects labor market outcomes only through changes in mental health.

also reduces life satisfaction of the partners by 1.0 point (13.4%), although the impact is statistically significant at only 10% level (Column (2)).

Next, we employ the unique data on refugee children in wave 3 and examine two child outcomes, mental health status and school performance. The medical literature suggests that the mental health of refugee parents has an important role in child refugee mental health (Fazel et al., 2012). For example, lack of parental support is shown to be a predictor of PTSD in children. Our study reaffirms this finding by showing that a one standard deviation increase in refugee mental health scores causes a 3.2 unit increase (35.4%) in the mental health score of their children (Column (3)). A one standard deviation increase in parental mental health scores also leads to a 1.6 percentage point (26.2%) increase in children's probability of having school performance below the average (Column (4)). This is consistent with previous findings for the general population showing that mothers' mental health is a strong predictor of their children's human capital accumulation (Johnston et al., 2013). Overall, these findings suggest that refugees with mental health issues have negative externalities on their family members' welfare outcomes.

5.2. Robustness tests

Our results are robust to a number of sensitivity checks. We briefly summarize the results here and offer more detailed results and discussion in Appendix B and in Tables A3-A16 (Appendix A). First, we estimate the linear FE and IV-FE models for employment status and other binary outcomes variables instead of the logit FE and IV-logit-FE models. Second, we analyze the original non-standardized mental health scores. Third, for the labor income regressions in Table 2, refugees who do not work are assumed to have zero incomes. Alternatively, we also analyze a subsample of workers that have positive incomes. Fourth, to address panel attrition issues, we use a balanced sample as well as model with longitudinal weights provided by BNLA. Fifth, while language skills are commonly employed in studies relating to labor market outcomes of refugees (e.g., Dagnelie et al., 2019; LoPalo, 2019), these variables might be endogenous so we exclude these variables from the regressions. Our results remain robust.

Sixth, we examine other (overall) health and physical health issues and find negative impacts of overall health, but no impact of physical health, on labor outcomes. Seventh, we construct alternative disaggregate measures of mental illness instead of the sum of the K6 items. Figure 2 examines each item separately to determine which dimension drives the effects of mental health. Using our preferred model specifications, we find that most of these dimensions of mental illness have a negative impact on employment status and labor income. We further create a dummy indicator to measure serious mental illness, defined as mental health score being greater than 19 (Chen et al., 2017). The results using the new measure remain qualitatively similar.

Eighth, we employ as a proxy for mental distress an indicator of PTSD available from the BNLA, which is an eight-item self-reported screening measure derived from the Harvard Trauma Questionnaire. We also address potential self-selection into LFP and subsequent employment status by employing the alternative two-part fractional response model (Roodman, 2011). To help alleviate potential reverse causality (i.e., mental health and labor market outcomes are measured in the same survey wave), we regress labor market outcomes on mental illness measured in the previous wave (i.e., wave *t-1*). These checks provide qualitatively similarly results (albeit weaker statistical significance for labor incomes for the last check).

Ninth, we investigate whether the main effects of mental illness on refugee labor outcomes are shaped by their employment experience before arrival. For example, those used to be in paid employment may find easier to get a job in the host country, and such experience may also affect their mental health status. In our model specification, this has been taken into account by controlling for individual characteristics and individual fixed effects. We implement a further check by splitting our sample into two groups based on whether they did any paid work before arrival and find qualitatively similar results.

Finally, we conduct various checks on the IV. Firstly, we add up the total number of traumatic events experienced by refugees as an alternative instrument for mental health. Secondly, we test the robustness of our results to deviations from the assumption of perfect exogeneity, using Conley et al.'s (2012) bounding method. These tests produce similar results.

5.3. Heterogeneity analysis

An important policy question is whether some sub-groups of refugees are particularly vulnerable to the impacts of mental illness. We examine several characteristics of refugees in this section. First, we examine the differential impacts of mental health based on visa types, which are classified into onshore and offshore visas. The offshore resettlement program applies to people living in other countries who have been identified as refugees by UNHCR and referred to Australia for resettlement, while the onshore protection program is available to people seeking asylum who arrived in Australia with or without a valid visa. The latter group is recognized to be more vulnerable given that they might be subjected to detention. Indeed, results in Panel A of Table 5 show that those who were granted onshore visas have worse labor market outcomes, subjected to an increase in mental health score.

Next, we are interested in the time that refugees spent in Australia and examine whether it has an important role in the relationship between mental health and labor market outcomes. In our sample, approximately 76.4% of respondents had been in Australia fewer than five months before the time of the first interview. It is reasonable to argue that these newly arrived residents do not have sufficient time for resettlement, and thus are more vulnerable than those who arrived earlier. Results in Panel B of Table 5 confirm our expectation. We then examine whether those who spent more time in refugee camps are more susceptible to the impacts of mental illness. This hypothesis is supported by the results shown in Panel C of Table 5. We also look at other background characteristics of refugees including their country of origins, and whether they currently live in a major city in Australia. The results in Panels D and E provide little support for these hypotheses. An exception is that refugees from Sub-Saharan Africa appear to be less vulnerable than those from the Middle East regarding the impacts of mental illness on labor income, but the result is marginally statistically significant at the 10% level.

Another important factor for refugees is social network. Previous studies have shown that immigrants with larger networks are more successful in the labor market (e.g., Munshi, 2003). In the context of humanitarian migrants, Beaman (2012) examines labor market integration of refugees who just arrived in the United States and finds that an increase in the number of recent refugees worsens the labor market outcomes of newly-arrived refugees, while an increase in the number of tenured refugees improves them. Dagnelie et al. (2019) find that the probability that refugees are employed 90 days after arrival is positively affected by the number of business owners in their network, but negatively affected by the number who are employees. We thus construct a "network" variable that indicates whether refugees had no family members or friends in the host country before they came. The interaction term between mental health scores and this network variable is negative and statistically significant (Panel F), which shows that, relative to those who have a network, increases in mental health scores of refugees without a network have a larger negative effect on the probability of employment and labor income.

Next, we examine the role of government and community supports in mediating the impacts of mental illness on labor outcomes. As discussed in Section 2, the Australian government has implemented several programs to improve refugee employment integration. While we are unable to identify participants to these programs in the BNLA survey, we employ a variable indicating whether they receive government benefits as a simple proxy. We also use information on whether refugees receive assistance from ethnic or religious communities to construct an indicator of local community support. The summary statistics presented in Table 1 show that about 53.4% of refugees in our sample receive benefits from the government, while that number is lower for those who receive support from the local community (49.8%).

The results in Panel G provide strong evidence for the beneficial role of government support. Specifically, we find that the impacts of mental health issues on labor outcomes are less pronounced for those receiving support from the government. This is consistent with findings from previous studies showing that government aid helps refugees better integrate into the labor market (e.g., LoPalo, 2019). Our findings are particularly important given that most respondents in our sample are newly arrived refugees who may have fewer resources, and thus are more vulnerable. However, we find no evidence of such impacts for local community support, as shown in Panel H.

Our findings so far have provided strong evidence of the effects of poor mental health on refugees' labor outcomes. While the BNLA survey does not allow us to examine whether the mental health impacts are more pronounced for refugees than other groups, we explore a quick comparison between migrants and the general population using longitudinal data from the HILDA survey over the period 2001-2019. Migrants in this survey are identified based on their country of birth. We create an interaction term between migrant status and mental health score with the latter being measured by the Mental Health Inventory (MHI-5) scale. Employing the non-IV individual FE model, we find a negative correlation between mental illness and labor outcomes for both population groups, but no evidence of differential impacts between the groups (Appendix A, Table A17). This finding, however, should be interpreted with caution given the endogeneity of mental health.

6. Conclusions

The wide-ranging labor market consequences associated with mental illness have been well documented in the literature. However, hardly any economic study currently exists on the causal effects of mental health on refugee labor market outcomes. Understanding this relationship is important given that many richer countries are facing a large influx of refugees. We provide an early study that identifies the causal effects of mental illness on refugees by instrumenting for it with past exposure to traumatic events interacted with time after resettlement, which is further strengthened with individual fixed effects.

Our findings indicate that worse mental health lowers the probability of having paid employment and labor income. Worse mental health also reduces LFP, job quality, and life satisfaction and exerts negative externalities on refugee partners and children. Yet, these effects appear more pronounced for refugees who recently arrived or are without a social network. At the same time, the effects are weaker for those who receive benefits from the government. This highlights the beneficial role of government support programs in reducing the negative impacts of mental health issues on labor outcomes and in improving refugees' integration, especially if these programs are targeted at newly arrived refugees or refugees who do not have a social network to rely on.

Future directions of research can focus on experimenting with and evaluating the impacts of tailor-made programs that are targeted at improving refugees' mental health and their social networks. Furthermore, we still know little about the heterogeneous characteristics of the firms that employ refugees (e.g., in the informal or formal sectors, small firms or large firms), which could be amenable to government support to further enhance their efficiency.

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Table 1: Data sources and summary statistics

Variable	Descriptions	Mean	Standard deviation	Min	Max
Main outcomes					
Employment status	= 1 employed in a paid job in the last seven days; 0 = otherwise	0.455	0.498	0.000	1.000
Labor income	Weekly (real) income from all jobs in $1,000 AUD.	0.716	0.429	0.000	4.598
Other outcomes					
Labor force participation (LFP)	= 1 if employed in a paid job in the last seven days, or looked for a paid job in the past four weeks, 0 otherwise	0.418	0.493	0.000	1.000
Permanent job	= 1 if working on permanent job, 0 otherwise	0.163	0.370	0.000	1.000
Skilled occupation	= 1 if having a skilled occupation, 0 otherwise	0.135	0.342	0.000	1.000
Agriculture	= 1 if working in agricultural sector, 0 otherwise	0.746	0.435	0.000	1.000
Number of work hours per week	Total number of work hours per week	32.654	13.876	1.000	125.000
Life satisfaction	0 (Completely dissatisfied) – 10 (Completely satisfied)	7.597	2.120	0.000	10.000
Partner labor force participation	= 1 if partner was employed in a paid job in the last seven days, or looked for a paid job in the past four weeks, 0 otherwise	0.200	0.400	0.000	1.000
Partner life satisfaction	0 (Completely dissatisfied) – 10 (Completely satisfied)	7.608	2.014	1.000	10.000
Child mental health	Kessler 6 total score of children	8.954	5.323	0.000	29.000
Child education performance below average	= 1 if overall achievement at school is below average, 0 otherwise	0.061	0.240	0.000	1.000
Mental health measures					
Mental health	Kessler 6 Total Score	11.695	5.513	6.000	30.000
Mental health - nervous	Feeling nervous in the last four weeks (1. None of the time; 2. A little of the time; 3. Some of the time; 4. Most of the time; 5. All of the time).	2.101	1.151	1.000	5.000
Mental health - hopeless	Feeling hopeless in the last four weeks (1. None of the time; 2. A little of the time; 3. Some of the time; 4. Most of the time; 5. All of the time).	1.825	1.117	1.000	5.000
Mental health - restless	Feeling restless or fidgety in the last four weeks (1. None of the time; 2. A little of the time; 3. Some of the time; 4. Most of the time; 5. All of the time).	1.960	1.165	1.000	5.000
Mental health - effort	Feeling that everything was an effort in the last four weeks (1. None of the time; 2. A little of the time; 3. Some of the time; 4. Most of the time; 5. All of the time).	2.426	1.430	1.000	5.000

Mental health - cheer	Feeling that nothing could cheer you up in the last four weeks (1. None of the time; 2. A little of the time; 3. Some of the time; 4. Most of the time; 5. All of the time).	1.871	1.148	1.000	5.000
Mental health - worthless	Feeling worthless in the last four weeks (1. None of the time; 2. A little of the time; 3. Some of the time; 4. Most of the time; 5. All of the time).	1.512	0.971	1.000	5.000
Control variables					
18-22	Age groups	0.143	0.351	0.000	1.000
23-27		0.179	0.384	0.000	1.000
28-32		0.169	0.375	0.000	1.000
33-37		0.155	0.362	0.000	1.000
38-42		0.133	0.340	0.000	1.000
43-47		0.115	0.319	0.000	1.000
48-52		0.068	0.251	0.000	1.000
53 and older		0.037	0.189	0.000	1.000
Marital status	= 1 if married, 0 otherwise	0.569	0.495	0.000	1.000
Household size	Number of household members	3.918	2.080	1.000	15.000
English - listening	English speaking proficiency (1. Very Well; 2. Well; 3. Not well; 4. Not at all)	2.292	0.760	1.000	4.000
English - speaking		2.387	0.763	1.000	4.000
English - reading		2.366	0.816	1.000	4.000
English - writing		2.446	0.825	1.000	4.000
Home ownership	= 1 if homeowner, 0 otherwise	0.143	0.351	0.000	1.000
Other variables (heterogeneity analysis)					
Visa type	= 1 if refugee; 0 if other humanitarian protections	0.622	0.485	0.000	1.000
Migration pathway	= 1 if onshore; 0 if offshore	0.247	0.431	0.000	1.000
Time in Australia	= 1 if less than a year, 0 otherwise	0.764	0.425	0.000	1.000
Camp	= 1 if spent time in refugee camp before arrival, 0 otherwise	0.229	0.420	0.000	1.000
Residence area	= 1 if living in remote areas, 0 if major cities	0.100	0.300	0.000	1.000
Network	= 1 if having social network before arrival, 0 otherwise	0.681	0.466	0.000	1.000
Government benefit	= 1 if receving government benefits, 0 otherwise	0.534	0.499	0.000	1.000

Local community support	= 1 if receving local community benefits, 0 otherwise	0.498	0.500	0.000	1.000
Instrument					
Trauma experience	= 1 if experiencing any trauma before arrived, 0 otherwise	0.896	0.305	0.000	1.000
Number of observations		3,687			
Number of individuals		1,609			

Table 2: Impacts of mental health on labor outcomes

Dependent variable:	Employment status		Weekly labor income ($1,000 AUD)	
	Logit-FE	IV-Logit-FE	FE	IV-FE
	(1)	(2)	(3)	(4)
Standardized mental health scores	-0.046***	-0.064***	-0.005***	-0.192***
	(0.009)	(0.009)	(0.001)	(0.055)
First stage of 2SLS (dependent variable is standardized mental health scores)				
Trauma experience*Year after arrival		-0.039***		-0.058***
		(0.009)		(0.016)
Kleibergen-Paap F stat.		17.692		19.635
AR 95-CIs		[-0.111, -0.031]		[-0.400, -0.124]
Adjusted *p*-value	0.000	0.000	0.001	0.011
Dep. Mean	0.455	0.455	0.716	0.716
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations	3,687	3,687	3,687	3,687
Number of individuals	1,609	1,609	1,609	1,609

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results in Columns (1) and (2) are presented as marginal effects. Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38. Full estimation results are reported in Table A1 (Appendix A). The adjusted *p*-value describes a conservative (upper bound) probability that rejecting the null hypothesis will result in one or more Type I errors, as implemented in Newson (2010).

Table 3: Impacts of mental health on other labor and life satisfaction outcomes

Dependent variable:	Labor force participation	Permanent job	Skilled occupation	Work in agriculture	Number of work hours per week	Life satisfaction
	(1)	(2)	(3)	(4)	(5)	(6)
Standardized mental health scores	-0.035***	-0.011	-0.032***	0.056***	-10.146***	-0.602**
	(0.005)	(0.007)	(0.007)	(0.008)	(1.691)	(0.301)
First stage of 2SLS (dependent variable is standardized mental health scores)						
Trauma experience* Year after arrival	-0.023***	-0.039***	-0.039***	-0.039***	-0.058***	-0.058***
	(0.006)	(0.009)	(0.009)	(0.009)	(0.016)	(0.018)
Kleibergen-Paap F stat.	35.644	17.692	17.692	17.692	19.635	79.537
AR 95-CIs	[-0.059, -0.025]	[-0.039, 0.006]	[-0.145, -0.017]	[0.028, 0.147]	[-20.869, -6.287]	[-1.003, -0.256]
Dep. Mean	0.418	0.163	0.135	0.746	32.836	7.597
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,768	3,687	3,687	3,687	3,687	6,392
Number of individuals	2,182	1,609	1,609	1,609	1,609	2,060

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model (marginal effects) in Columns (1)-(4) and IV-FE model in Columns (5)-(6). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38. Permanent job is defined as working fulltime/parttime with permanent contract (the reference group is fixed-term contract and casual employment). Skilled occupation is defined as jobs with occupational scales above medium.

Table 4: Impacts of mental health on refugee partners' and children's outcomes

Dependent variable:	Partner employment status	Partner life satisfaction	Child mental health scores	Child school performance below average
	(1)	(2)	(3)	(4)
Standardized mental health scores	-0.004	-1.018*	3.170*	0.016***
	(0.005)	(0.570)	(1.756)	(0.005)
First stage of 2SLS (dependent variable is standardized mental health scores)				
Trauma experience*Year after arrival	-0.023***	-0.228*		
	(0.006)	(0.130)		
Trauma experience			0.537***	0.415***
			(0.183)	(0.133)
Kleibergen-Paap F stat.	35.644	28.205	8.766	9.710
AR 95-CIs	[-0.014, 0.004]	[-2.406, -0.465]	[-0.582, 8.685]	[0.001, 0.476]
Dep. Mean	0.200	7.608	8.954	0.061
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations	5,297	1,663	351	587
Number of individuals	1,384	986	351	587

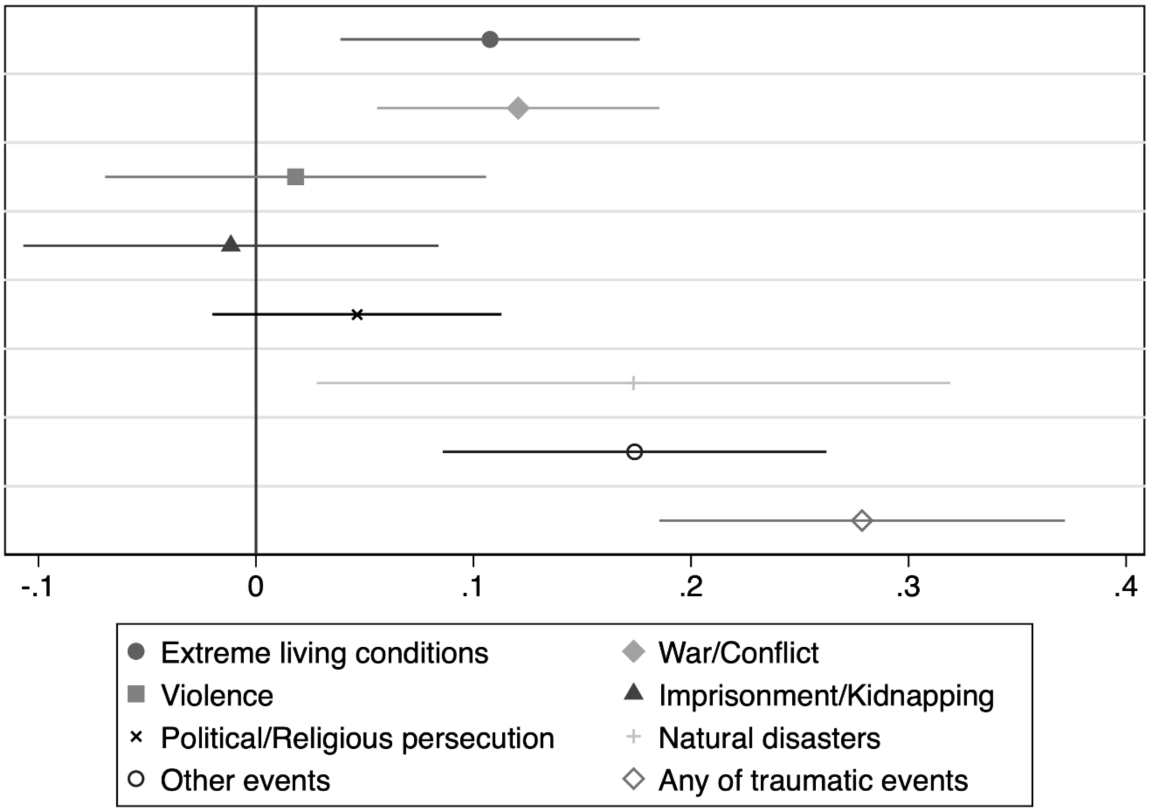
Notes: *** p<0.01, ** p<0.05, * p<0.1. Columns (1) and (2) show results of IV-Logit-FE (marginal effects) and IV-FE models, columns (3) and (4) show results of IV model using data from wave 3 of the BNLA. Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one.

Table 5: Heterogeneity analysis

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Panel A: Visa type (Onshore vs offshore)		
Standardized mental health scores*Onshore	-0.002**	-0.041***
	(0.001)	(0.014)
Panel B: Time in Australia		
Standardized mental health scores*Less than 1 year	-0.081***	-0.038***
	(0.027)	(0.012)
Panel C: Spent time in refugee camp before arrival		
Standardized mental health scores*Spent time in camp	-0.004*	-0.044**
	(0.002)	(0.022)
Panel D: Country of origin (Reference: Middle East)		
Standardized mental health scores*South-East Asia	0.025	0.001
	(0.074)	(0.002)
Standardized mental health scores*Southern and Central Asia	0.044	0.000
	(0.076)	(0.003)
Standardized mental health scores*Sub-Saharan Africa	0.113	0.006*
	(0.089)	(0.003)
Panel E: Major city vs regional Australia		
Standardized mental health scores*Residence area	0.772	-0.141
	(28.106)	(0.416)
Panel F: Social network before arrival		
Standardized mental health scores*No network	-0.098***	-0.031***
	(0.031)	(0.008)
Panel G: Government benefit received		
Standardized mental health scores*Not received	-0.001***	-0.0002*
	(0.0002)	(0.0001)
Panel H: Local community support		
Standardized mental health scores*No support	-0.011	-0.00005
	(0.008)	(0.0006)

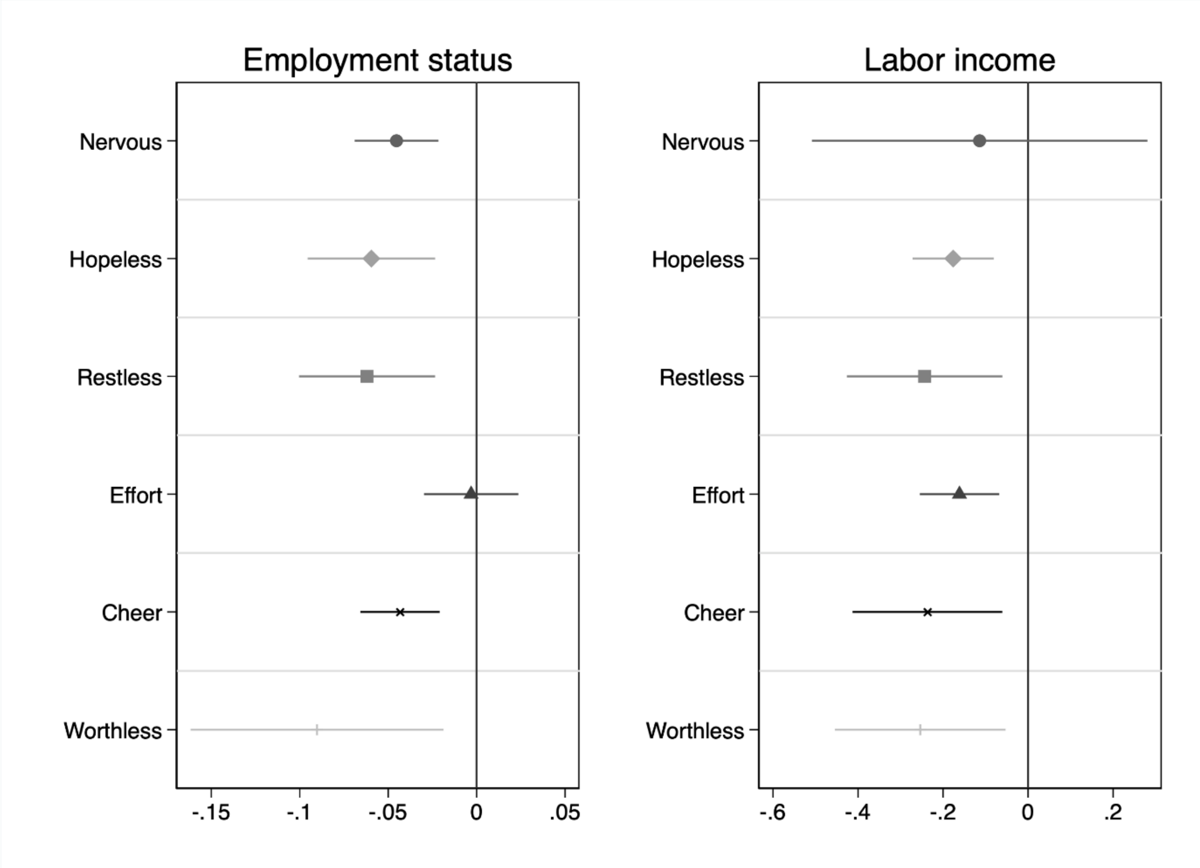
Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one.

Figure 1: Impacts of different trauma experiences on mental illness



Notes: The figure plots the estimated impacts of trauma experience and their 95% CIs on standardized mental health scores using OLS model. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one.

Figure 2: Dimensions of mental health



Notes: The figures plot the estimated impacts and their 95% CIs for six dimensions of mental health on labor market outcomes using IV-Logit-FE model (marginal effects) for employment status and IV-FE model for weekly labor income ($1,000 Australian dollars). Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership.

Appendix A: Additional Tables and Figures

Table A1: Impacts of mental health on labor outcomes – Full estimation results

Dependent variable:	Employment status		Weekly labor income ($1,000 AUD)	
	Logit-FE	IV-Logit-FE	FE	IV-FE
	(1)	(2)	(3)	(4)
Standardized mental health scores	-0.046***	-0.064***	-0.005***	-0.192***
	(0.009)	(0.009)	(0.001)	(0.055)
Age groups (Ref: 18-22)				
23-27	0.221***	0.058	0.012***	0.012
	(0.074)	(0.646)	(0.004)	(0.018)
28-32	0.592***	0.159	0.038***	0.023
	(0.061)	(0.914)	(0.006)	(0.024)
33-37	0.716***	0.251	0.075***	0.053*
	(0.066)	(0.998)	(0.008)	(0.029)
38-42	0.733***	0.312	0.108***	0.061
	(0.071)	(1.002)	(0.011)	(0.039)
43-47	0.737***	0.359	0.131***	0.101**
	(0.073)	(1.008)	(0.011)	(0.042)
48-52	0.739***	0.425	0.158***	0.151***
	(0.074)	(2.643)	(0.013)	(0.051)
53 and older	0.739***	0.494	0.177***	0.175***
	(0.074)	(3.407)	(0.015)	(0.063)
Married	0.034	0.042	0.010**	-0.009
	(0.023)	(0.026)	(0.004)	(0.016)
Household size	-0.003	-0.004	0.004***	0.004*
	(0.004)	(0.004)	(0.001)	(0.002)
English - listening	0.032*	0.043**	0.007***	0.011
	(0.017)	(0.018)	(0.002)	(0.008)
English - speaking	0.056***	0.075***	0.006**	0.010
	(0.019)	(0.019)	(0.002)	(0.010)
English - reading	0.003	0.007	-0.003	0.013
	(0.018)	(0.019)	(0.002)	(0.011)
English - writing	0.023	0.029	0.001	0.002
	(0.017)	(0.019)	(0.002)	(0.010)
Homeowner	0.061	0.083*	0.019***	0.014
	(0.041)	(0.044)	(0.005)	(0.014)
Residence area	0.058*	0.077**	-0.001	-0.009
	(0.033)	(0.036)	(0.007)	(0.022)
First stage of 2SLS (dependent variable is Standardized mental health scores)				
Trauma experience*Year after arrival		-0.039***		-0.058***
		(0.009)		(0.016)
Kleibergen-Paap F stat.		17.692		19.635
AR 95-CIs		[-0.111, -0.031]		[-0.400, -0.124]
Adjusted *p*-value	0.000	0.000	0.001	0.011
Dep. Mean	0.455	0.455	0.716	0.716
Individual FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes

Observations	3,687	3,687	3,687	3,687
Number of individuals	1,609	1,609	1,609	1,609

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results in Columns (1) and (2) are presented as marginal effects. Standard errors in parentheses are clustered at the individual level. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38. The adjusted *p*-value describes a conservative (upper bound) probability that rejecting the null hypothesis will result in one or more Type I errors, as implemented in Newson (2010).

Table A2: Impacts of mental health on labor outcomes – Coefficient estimate of IV-Logit-FE model

Dependent variable:	Employment status	Labor force participation	Permanent job	Skilled occupation	Work in agriculture
	(1)	(2)	(3)	(4)	(5)
Standardized mental health scores	-0.765***	-0.542***	-0.185	-0.680***	0.746***
	(0.108)	(0.079)	(0.120)	(0.143)	(0.112)
First stage of 2SLS (dependent variable is standardized mental health scores)					
Trauma experience*Year after arrival	-0.039***	-0.023***	-0.039***	-0.039***	-0.039***
	(0.009)	(0.006)	(0.009)	(0.009)	(0.009)
Kleibergen-Paap F stat.	17.692	35.644	17.692	17.692	17.692
Dep. Mean	0.455	0.418	0.163	0.135	0.746
Other controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes
Observations	3,687	7,768	3,687	3,687	3,687
Number of individuals	1,609	2,182	1,609	1,609	1,609

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model. Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38. Permanent job is defined as working fulltime/parttime with permanent contract (the reference group is fixed-term contract and casual employment). Skilled occupation is defined as jobs with occupational scales above medium.

Table A3: Impacts of mental health on labor outcomes – Results of FE and IV-FE models

	Employment status		Labor force participation		Permanent job		Skilled occupation		Work in agriculture	
VARIABLES	FE	IV-FE	FE	IV-FE	FE	IV-FE	FE	IV-FE	FE	IV-FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Standardized mental health scores	-0.082***	-1.947***	-0.033***	-2.657**	-0.010	-0.443	-0.039***	-0.600***	0.068***	1.329***
	(0.013)	(0.544)	(0.006)	(1.086)	(0.011)	(0.273)	(0.010)	(0.189)	(0.012)	(0.385)
First stage of 2SLS (dependent variable is standardized mental health scores)										
Trauma experience*Year after arrival		-0.058***		-0.058***		-0.058***		-0.058***		-0.058***
		(0.016)		(0.016)		(0.016)		(0.016)		(0.016)
Kleibergen-Paap F stat.		17.692		17.692		17.692		17.692		17.692
AR 95-CIs		[-4.014, -1.262]		[-10.924, -1.498]		[-1.811, -0.070]		[-1.355, -0.351]		[0.837, 2.754]
Dep. Mean	0.455	0.455	0.418	0.418	0.163	0.163	0.135	0.135	0.746	0.746
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,687	3,687	7,768	7,768	3,687	3,687	3,687	3,687	3,687	3,687
Number of individuals	1,609	1,609	2,182	2,182	1,609	1,609	1,609	1,609	1,609	1,609

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A4: Impacts of mental health on labor outcomes – Non-standardized mental health score

Dependent variable:	Employment status		Weekly labor income ($1,000 AUD)	
	Logit-FE	IV-Logit-FE	FE	IV-FE
	(1)	(2)	(3)	(4)
Mental health scores	-0.008***	-0.011***	-0.0008***	-0.032***
	(0.002)	(0.001)	(0.0002)	(0.009)
First stage of 2SLS (dependent variable is non-standardized mental health scores)				
Trauma experience*Year after arrival		-0.229***		-0.347***
		(0.053)		(0.096)
Kleibergen-Paap F stat.		17.692		19.635
AR 95-CIs		[-0.023, -0.007]		[-0.067, -0.021]
Dep. Mean	0.455	0.455	0.716	0.716
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations	3,687	3,687	3,687	3,687
Number of individuals	1,609	1,609	1,609	1,609

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results in Columns (1) and (2) are presented as marginal effects. Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A5: Impacts of mental health on labor income – Sample of workers with positive incomes

Dependent variable:	Weekly labor income ($1,000 AUD)	
	FE	IV-FE
	(1)	(2)
Standardized mental health scores	-0.004*	-0.233**
	(0.002)	(0.110)
First stage of 2SLS (dependent variable is standardized mental health scores)		
Trauma experience*Year after arrival		-0.064**
		(0.028)
Kleibergen-Paap F stat.		55.517
AR 95-CIs		[-2.023, -0.112]
Dep. Mean	0.716	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	1,772	1,772
Number of individuals	843	843

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of FE model in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A6: Attrition test – Balanced sample

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Standardized mental health scores	-0.048***	-0.200***
	(0.010)	(0.065)
First stage of 2SLS (dependent variable is standardized mental health scores)		
Trauma experience*Year after arrival	-0.044***	-0.063***
	(0.011)	(0.020)
Kleibergen-Paap F stat.	17.627	19.635
AR 95-CIs	[-0.094, -0.019]	[-0.469, -0.124]
Dep. Mean	0.455	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	2,497	2,497
Number of individuals	1,003	1,003

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A7: Impacts of mental health on labor outcomes – Weighted regression

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Standardized mental health scores	-0.058***	-0.188***
	(0.009)	(0.057)
First stage of 2SLS (dependent variable is standardized mental health scores)		
Trauma experience*Year after arrival	-0.043***	-0.058***
	(0.011)	(0.017)
Kleibergen-Paap F stat.	21.383	21.383
AR 95-CIs	[-0.111, -0.031]	[-0.400, -0.124]
Dep. Mean	0.455	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	3,687	3,687
Number of individuals	1,609	1,609

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A8: Impacts of mental health on labor outcomes – Excluding language skills variables

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Standardized mental health scores	-0.067***	-0.183***
	(0.009)	(0.046)
First stage of 2SLS (dependent variable is standardized mental health scores)		
Trauma experience*Year after arrival	-0.045***	-0.066***
	(0.009)	(0.016)
Kleibergen-Paap F stat.	17.692	19.635
AR 95-CIs	[-0.095, -0.032]	[-0.334, -0.123]
Dep. Mean	0.455	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	3,687	3,687
Number of individuals	1,609	1,609

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A9: Impacts of overall health and physical health

Dependent variable:	Employment status		Weekly labor income ($1,000 AUD)	
	(1)	(2)	(3)	(4)
Overall health issue	-0.020**		-0.002***	
	(0.008)		(0.001)	
Physical health issue		-0.010		-0.030*
		(0.165)		(0.017)
First stage of 2SLS				
Trauma experience*Year after arrival	-0.001***	-0.0001***	-0.001***	-0.0001***
	(0.0002)	(0.00003)	(0.0002)	(0.00003)
Kleibergen-Paap F stat.	24.517	7.652	24.517	7.652
AR 95-CIs	[-0.040, -0.005]	[-0.386, 0.545]	[-0.005, -0.001]	[-0.106, -0.002]
Dep. Mean	0.455	0.455	0.716	0.716
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations	3,687	1,863	3,687	1,863
Number of individuals	1,609	1,147	1,609	1,147

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model (marginal effects) in Columns (1)-(2) and IV-FE model in Columns (3)-(4). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A10: Impacts of mental health on labor outcomes: Impacts of mental health on labor outcomes – Dummy indicator

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Serious mental illness	-0.064***	-0.423***
	(0.014)	(0.159)
First stage of 2SLS (dependent variable is serious mental illness)		
Trauma experience*Year after arrival	-0.023***	-0.026***
	(0.005)	(0.010)
Kleibergen-Paap F stat.	17.312	16.988
AR 95-CIs	[-0.304, -0.039]	[-1.414, -0.244]
Dep. Mean	0.455	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	3,687	3,687
Number of individuals	1,609	1,609

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A11: Impacts of mental health on labor outcomes – Post-traumatic stress disorder

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Post-traumatic stress disorder	-0.035**	-0.599**
	(0.017)	(0.264)
First stage of 2SLS (dependent variable is post-traumatic stress disorder)		
Trauma experience*Year after arrival	-0.018***	-0.019**
	(0.005)	(0.008)
Kleibergen-Paap F stat.	19.070	47.439
AR 95-CIs	[-0.202, -0.017]	[-3.882, -0.318]
Dep. Mean	0.455	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	3,687	3,621
Number of individuals	1,609	1,593

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A12: Fractional regression

Dependent variable:	Labor force participation	Employment status
	(1)	(2)
Standardized mental health scores	-0.011***	-0.069***
	(0.001)	(0.006)
Dep. Mean	0.418	0.455
Other controls	Yes	Yes
Survey wave FE	Yes	Yes
Observations	7,768	3,893

Notes: *** p<0.01, ** p<0.05, * p<0.1. The fractional regression is conducted by using Stata command '*cmp*' developed by Roodman (2011). Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one.

Table A13: Impacts of mental health on labor outcomes – Mental health at time *(t-1)*

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Standardized mental health scores at *(t-1)*	-0.049***	-0.144*
	(0.005)	(0.079)
First stage of 2SLS (dependent variable is standardized mental health scores)		
Trauma experience*Year after arrival	-0.041***	-0.085*
	(0.012)	(0.045)
Kleibergen-Paap F stat.	16.972	18.444
AR 95-CIs	[-0.094, -0.025]	[-0.295, -0.084]
Dep. Mean	0.455	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	2,805	2,805
Number of individuals	1,406	1,406

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A14: Impacts of mental health on labor outcomes – Past-employment experience

Dependent variable:	Employment status		Weekly labor income ($1,000 AUD)	
	No work experience	Have work experience	No work experience	Have work experience
	(1)	(2)	(3)	(4)
Standardized mental health scores	-0.027*	-0.078***	-0.131**	-0.293***
	(0.014)	(0.011)	(0.062)	(0.083)
First stage of 2SLS				
Trauma experience*Year after arrival	-0.044**	-0.040***	-0.050**	-0.046***
	(0.017)	(0.011)	(0.022)	(0.013)
Kleibergen-Paap F stat.	15.150	17.151	15.670	16.416
AR 95-CIs	[-0.117, -0.008]	[-0.195, -0.010]	[-0.237, -0.074]	[-0.663, -0.169]
Dep. Mean	0.455	0.455	0.716	0.716
Other controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations	1,238	2,429	1,238	2,429
Number of individuals	684	915	684	915

Notes: *** p<0.01, ** p<0.05, * p<0.1. Results of IV-Logit-FE model (marginal effects) in Columns (1)-(2) and IV-FE model in Columns (3)-(4). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Table A15: Impacts of mental health on labor outcomes – Intensity of trauma experience

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Standardized mental health scores	-0.064***	-0.361**
	(0.009)	(0.157)
First stage of 2SLS (dependent variable is standardized mental health scores)		
Trauma experience (intensity)*Year after arrival	-0.009***	-0.009**
	(0.003)	(0.004)
Kleibergen-Paap F stat.	23.158	28.882
AR 95-CIs	[-0.273, -0.041]	[-1.396, -0.205]
Dep. Mean	0.455	0.716
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	3,687	3,687
Number of individuals	1,609	1,609

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Results of IV-Logit-FE model (marginal effects) in Column (1) and IV-FE model in Column (2). Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. The critical value of the F-test from Stock and Yogo (2005) is 16.38. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one.

Table A16: Plausibly exogenous instrument regressions

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Standardized mental health scores	-0.064***	-0.192***
	(0.009)	(0.055)
Lower bound	-0.076	-0.271
Upper bound	-0.022	-0.093

Notes: The lower bound and upper bound are estimated using the *plausexog* command in Stata developed by Clarke and Matta (2018). Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one.

Table A17: Impacts of mental health on labor outcomes – HILDA survey

Dependent variable:	Employment status	Weekly labor income ($1,000 AUD)
	(1)	(2)
Standardized mental health scores	-0.034***	-0.030***
	(0.004)	(0.009)
Standardized mental health scores*Migrants	-0.005	-0.003
	(0.008)	(0.021)
Dep. Mean	0.804	1.556
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	38,239	38,239
Number of individuals	4,500	4,500

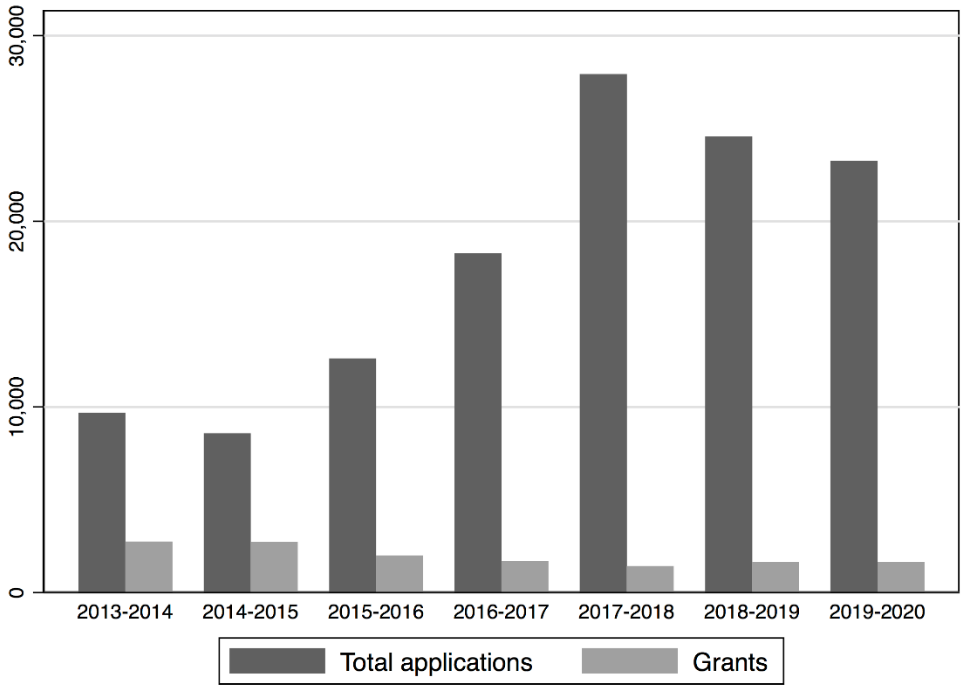
Notes: *** p<0.01, ** p<0.05, * p<0.1. Column (1) shows results of Logit-FE model (marginal effects). Column (2) shows results of FE model. Standard errors in parentheses are clustered at the individual level. Data is taken from HILDA survey (2001 – 2019). Control variables include age group dummy variables, marital status, education, and number of children. Mental health in the HILDA survey is measured using the five-item Mental Health Inventory (MHI-5) scale, with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one.

Table A18: Impacts of mental health on weekly labor income – Inverse hyperbolic sine transformation

Dependent variable:	Weekly labor income ($1,000 AUD)	
	FE	IV-Logit-FE
	(1)	(2)
Standardized mental health scores	-0.005***	-0.192***
	(0.001)	(0.055)
First stage of 2SLS (dependent variable is standardized mental health scores)		
Trauma experience*Year after arrival		-0.039***
		(0.009)
Kleibergen-Paap F stat.		19.635
AR 95-CIs		[-0.398, -0.123]
Dep. Mean	0.455	0.455
Other controls	Yes	Yes
Individual FE	Yes	Yes
Survey wave FE	Yes	Yes
Observations	3,687	3,687
Number of individuals	1,609	1,609

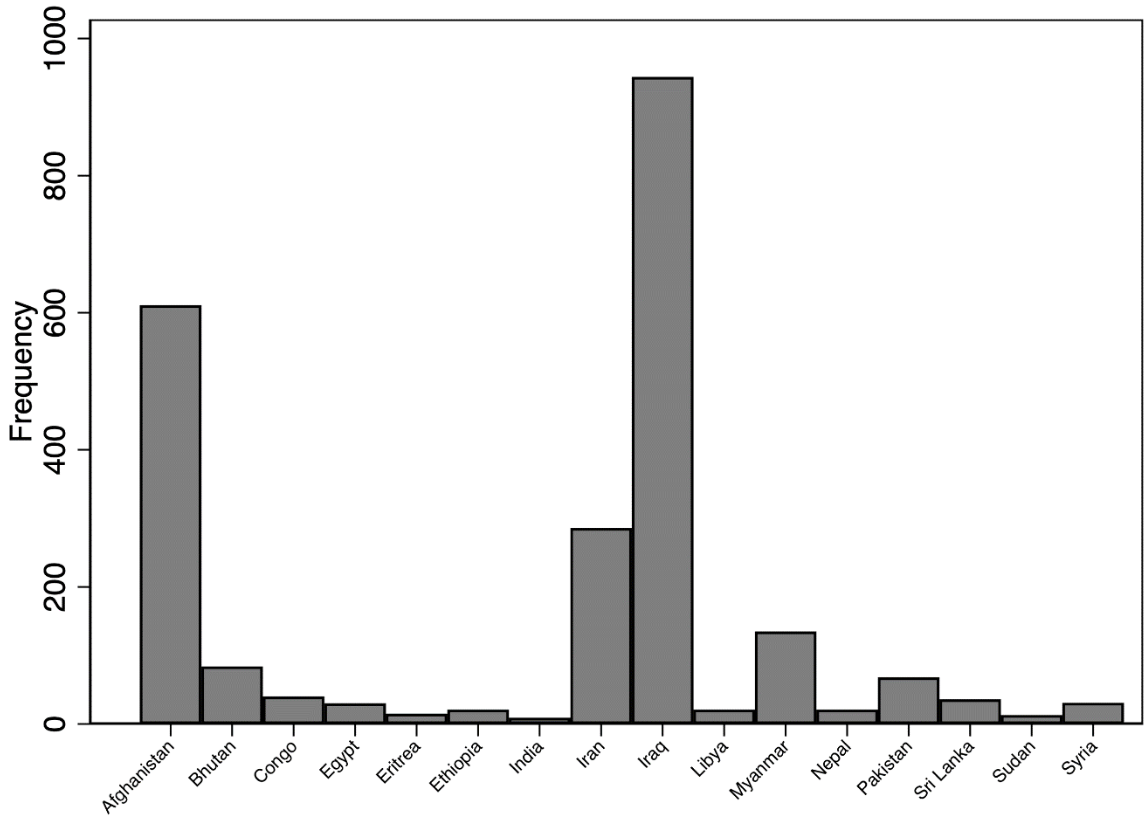
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses are clustered at the individual level. Control variables include age group dummy variables, marital status, household size, language skills (listening, speaking, reading, and writing), residence area, and home ownership. Mental health scores are the sum of the 6-item Kessler Psychological Distress Scale (K6), with a higher score indicating worse mental health. The scores are standardized to have a mean of zero and standard deviation of one. The critical value of the F-test from Stock and Yogo (2005) is 16.38.

Figure A1: Number of applications and grants of protection over time



Source: Department of Home Affairs (Australia).

Figure A2: Country of origin



Notes: Data from BNLA survey.

Appendix B: Robustness checks

To further scrutinize the robustness of our results, we conduct a battery of sensitivity analyses. These include checks with using the linear FE and IV-FE models instead of the logit FE and IV-logit-FE models, analyzing the original non-standardized mental health scores, removing workers with zero incomes, addressing panel attrition, and examining potential endogeneity of some covariates, whether the impacts are mitigated by other health channels other than mental health, alternative and disaggregate measures of mental distress, a different modeling approach, considering previous work experience, as well as implementing various stress tests on the IV.

First, we estimate the linear FE and IV-FE models for employment status and other binary outcomes variables instead of the logit FE and IV-logit-FE models and find qualitatively similar results. The results are presented in Table A3 (Appendix A). Second, our findings remain consistent when using the original non-standardized mental health scores, as shown in Table A4 (Appendix A). Third, for the labor income regressions in Table 2, refugees who do not work are assumed to have zero incomes. Alternatively, we also analyze a subsample of workers that have positive incomes and find consistent effects of mental illness (see Table A5, Appendix A).

Fourth, the panel attrition rate from wave 1 to wave 5 is approximately 22% and relatively lower than those in other surveys in Australia such as the HILDA or the Longitudinal Study of Australian Children (LSAC) (Department of Social Services, 2018). To address panel attrition issues, we create a balanced sample and replicate our main analysis in Table 2. The results confirm the negative impacts of mental illness on both employment status and labor income; furthermore, the estimates are of similar magnitudes (Appendix A, Table A6). In addition, we also account for the survey's stratified sampling design and nonresponse rates by using the longitudinal weights provided by BNLA. Again, the results of weighted regression reaffirm our previous findings, as shown in Table A7 (Appendix A).[19]

Fifth, while our baseline specification includes a range of covariates that are commonly employed in studies relating to labor market outcomes of refugees (e.g., Dagnelie et al., 2019; LoPalo, 2019), one may argue that language skills might be endogenous. For example, refugees who are eager to better engage in the labor market and have larger earnings might spend more effort on refining their language skills. We show that our results are robust to excluding these potential endogenous variables (Appendix A, Table A8).

Sixth, while our main interest is refugee mental illness, we also examine other (overall) health and physical health issues. In the BNLA survey, overall health is represented by an indicator denoting how refugees rated their health during the past four weeks before the interview. We recode the indicator so that it ranges from one ("excellent") to six ("very poor"). Similarly, physical health is captured by a categorical variable with higher values representing worse physical health. We find a negative impact of overall health issue on labor outcomes, while there is little evidence of the impact of physical health on the outcome variables (Appendix A, Table A9). This lends support to our main finding that mental health issues are the main barrier affecting refugee labor outcomes.

Seventh, we construct alternative disaggregate measures of mental illness instead of the sum of the K6 items in the main analysis. Figure 1 examines each item separately to determine which dimension drives the effects of mental health. Using our preferred model specifications, we find that most of these dimensions of mental illness have a negative impact on employment status (including "nervous", "hopeless", "restless", "cheer" and "worthless") and labor income (including "hopeless", "restless", "effort", "cheer", and "worthless"). We further create a

[19] We do not apply weights in the main analysis as the BNLA survey mainly focuses on refugees migrating to Australia within a year before the time of the first interview, and thus findings might not be generalized to all humanitarian migrants (Department of Social Services, 2017).

dummy indicator to measure serious mental illness, defined as mental health score being greater than 19 (Chen et al., 2017). The results using the new measure remain qualitatively similar (Appendix A, Table A10).

Eighth, we employ as a proxy for mental distress an indicator of PTSD available from the BNLA, which is an eight-item self-reported screening measure derived from the Harvard Trauma Questionnaire. Recent evidence suggests that PTSD symptoms are common among Syrian refugees in Norway (Aarethun et al., 2021). Participants rate PTSD symptoms on a four-point Likert scale (from 1 for "not at all" to four for "most of the time"), reporting how much the symptoms bothered them in the past week. We convert the answers into a dummy indicator that equals one if an individual is at risk of PTSD. The results remain qualitatively consistent (Appendix A, Table A11). The size of the coefficients in Table A11 also suggests that PTSD symptoms are strongly relevant for refugee respondents, and they have negative impacts on refugee employment outcomes.

Ninth, in the main analysis, we estimate the impact of worse mental health on employment status for refugees who participate in the labor force. To address potential self-selection into LFP and subsequent employment status, we employ the alternative two-part fractional response model (Roodman, 2011). While this approach allows us to model the LFP decision and employment status separately, it does not address the endogeneity of mental health. But our estimates remain qualitatively similar (Appendix A, Table A12).

Similarly, one may argue that mental health and labor market are measured in the same wave, which might lead to the problem of reverse causality (i.e., labor market exposure affects mental health). This is less likely to be the case in our study as we measure mental health in the last four weeks prior to the interview date, while labor outcomes are measured in the last seven days. To provide further support to our main findings, we regress labor market outcomes on mental illness measured in the previous wave (i.e., wave *t-1*) and find qualitatively similarly results, albeit weaker statistical significance for labor incomes (Appendix A, Table A13).

Another concern one may argue is that labor outcomes of refugees in the host country may be determined by their work experience before arrival, which in turn also has an impact on the trajectory of their mental illness. In our model specification, this has been taken into account by controlling for individual fixed effects. While other time-varying experience in the past is not available in the BNLA survey, we split our sample into two groups based on whether they did any paid work in a job, business or on a farm before arrival. The results presented in Table A14 (Appendix A) reveal no difference in the effect of mental health on labor outcomes for both groups.

Finally, we conduct various checks on the IV. Firstly, we add up the total number of traumatic events experienced by refugees as an alternative instrument for mental health. In other words, we consider the intensity of past traumatic experience rather than just exposure. Using this alternative measure produces similar results (Appendix A, Table A15). In fact, every additional traumatic episode has a large impact on both employment and income. Secondly, we test the robustness of our results to deviations from the assumption of perfect exogeneity, using Conley et al.'s (2012) bounding method. This method relaxes the assumption of perfect exogeneity and assumes a flexible second-stage regression that also includes the instrument as a regressor. Assuming that the direct effect of the instrument on labor outcomes ranges from zero—perfectly exogenous—to the reduced form effect, the lower bound and upper bound estimates are both negative (Appendix A, Table A16). We conclude that the negative impacts of mental illness on labor market outcomes are robust to a large degree of instrument endogeneity.

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