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Modelling Economic Policy Issues

Socioeconomic mental health disparities and income mobility in Australia: A longitudinal factor decomposition analysis

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ABSTRACT

In recent years mental health disparity has been rising in Australia. The contributing factors to this rising disparity are not well understood. We investigated this by measuring and decomposing socioeconomic mental health inequality in Australia using the Household, Income and Labour Dynamics in Australia (HILDA) panel survey datasets between 2009 and 2017 employing the longitudinal factor decomposition method. In this research, we decompose the Income-Related Health Mobility (IRHM) and the Health-Related Income Mobility (HRIM) index. The IRHM index reflects the effect of the relationship between relative health changes at a constant income level, and the HRIM index represents changes in income ranking or income mobility with a fixed health outcome over time. Our findings suggest that poorer individuals cannot procure private health insurance, experience more long-term health conditions and have larger exposure to life shocks than richer individuals. Thus, long-term health conditions, private health insurance coverage, and number of life disruptions are the primary factors that negatively impact the IRHM index, thereby contributing to an increase in socioeconomic inequality in mental health in Australia. Moreover, the HRIM index exhibits a more pronounced adverse impact from labour force status compared to the relatively weaker positive effects observed in the IRHM index, resulting in a net negative effect from labour force status in this period. To address this, Australian governments should focus on implementing cost-effective intervention policies targeting disadvantaged populations to maximise health system resources and minimise mental health disparity by addressing the socioeconomic determinants of mental health.

1. Introduction

The unequal distribution of health between the poor and better off individuals is a major concern in all countries. The Centers for Disease Control in the US and the European Commission have renewed their focus on socioeconomic health inequalities in response to growing demands for reducing health disparities (CDC, 2013; European Commission, 2013). Reducing health inequalities is germane to the health policy agenda of almost all countries. As an illustration, the Organization for Economic Co-operation and Development's (OECD) recent framework for policy action on inclusive growth recommends investing in individual's health to facilitate the transition towards an inclusive society and creates opportunities for all (OECD, 2019).

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The Social Determinants of Mental Health (SDoMH) are subtly different from those of physical health. SDoMH is a framework designed to comprehend and structure the diverse array of more detailed drivers and factors that play a role in mental health inequalities. In contrast to physical health, the member nations of the World Health Organization (WHO) often lack mental health policy framework. Approximately 72% of WHO member states have a standalone policy for mental health, while 57% have standalone laws (World Health Organization, 2018). The WHO calls for taking universal action on eliminating the social gradient in mental health outcomes for citizens in all its member states (World Health Organization and Calouste Gulbenkian Foundation, 2014). England, Scotland, New Zealand and Australia are some of the English-speaking high-income countries that have incorporated the SDoMH approach into their national policy settings and strategies (World Health Organization and Calouste Gulbenkian Foundation, 2014). An examination of mental health disparities in these countries should aid in the evaluation of existing policy measures.

2. Socioeconomic inequality in mental health

Inspired by Wagstaff et al. (2003)'s pioneering work on factor decomposition in health inequalities, a growing body of research has adopted similar approaches to unravel the complexities of socioeconomic inequalities in mental health. Early studies focused on core socioeconomic and demographic determinants like income, education, and employment, revealing diverse contributions across contexts. Studies like Lee and Jones (2007) in Taiwan and Morasae et al. (2012) in Iran highlighted the significance of factors including, employment and education. Further, Gunasekara et al. (2013) identified regional variations in key contributors, highlighting income, area deprivation, and labour force inactivity across Australia and New Zealand. Expanding beyond conventional factors, Amroussia et al. (2017) demonstrated the impact of psychosocial factors like discrimination and social support in the context of Sweden, while, León-Giraldo et al. (2021) in Colombia pinpointed conflict as a significant negative influence. Beyond general populations, research has also delved into specific groups, exploring inequalities among ethnic minorities (Hajizadeh et al., 2019), women (Christiani et al., 2015; Mutyambizi et al., 2019), migrants (Hong and Lee 2019) and older adults (Srivastava et al., 2021; Sun et al., 2021).

In Australia, poor mental health is a complex and pervasive problem. At a population level, health loss due to mental illness is a staggering 708,146 disability adjusted life years (DALYs), costing A$150.8 billion annually (Productivity Commission, 2020; Mihalopoulos et al., 2021). Adding to the concern, individuals with low income experience a 11.38% higher prevalence of mental disorders compared to those who are wealthy (Hashmi et al., 2021) and this socioeconomic inequality in mental health in Australia is deteriorating over time (Hashmi et al., 2020; Bishop et al., 2023; Botha et al., 2023). In spite of recent substantial reforms in the provision of mental healthcare, studies also revealed a significant rise in unmet needs for psychiatric care utilisation over the past decade (Meadows et al., 2015; Gao et al., 2023; Hashmi et al., 2023). Given this context, questions arise regarding the primary causes of this shift in mental health inequality. Thus, the objective of this study is to investigate the factors that are driving socio-economic inequality in mental health in Australia. More specifically, this study addresses the following research questions:

1. To what extent are changes in income and health (income-related health mobility and health-related income mobility) contributing to changes in socioeconomic inequality in mental health in Australia?
2. What are the major factors that drive income related health mobility and health related income mobility and consequently, contributing toward socioeconomic inequality in mental health in Australia?

The longitudinal analysis of socioeconomic inequalities in mental health has traditionally relied on techniques like Oaxaca-Blinder decomposition, offering valuable insights but overlooking critical aspects such as health and income mobility (Zeng and Jian, 2019; Linder et al., 2020; León-Giraldo et al., 2021). Recognizing this limitation, our paper leverages a recently developed longitudinal framework that explicitly allows us to account for these dynamic factors (Allanson et al., 2010; Siegel and Allanson, 2016). This framework uniquely allows to account for both income and health mobility, providing a much deeper understanding of the interplay between socioeconomic factors and mental health outcomes. Our work offers two significant contributions: firstly, it establishes a robust analytical framework for tackling this issue, and secondly, it sheds light on the key drivers of income-related mental health inequality in Australia. This crucial knowledge holds the potential to inform the development of targeted and effective policy interventions.

3. Methods

3.1. Bivariate rank dependent inequality indices

The Concentration Index serves as a bivariate rank-dependent measure of inequality. Its numerical range spans from $-\infty$ to ∞ when assessing absolute inequalities and from -1 to 1 for relative inequalities. When the ranking variable is income, a positive value implies that the outcome is concentrated among the rich, while a negative value suggests concentration among the poor. Suppose for a population of n individuals ($i = 1, 2, \ldots\ldots, n$) and T time periods ($t = 1, 2, \ldots\ldots, T$), the health outcome of interest is observed by h_{it} and socioeconomic achievement is observed by y_{it}. Given, the lower bound $l_h \geq 0$, the health outcome set is $h \in [l_h, u_h]$ if bounded and $h \in [l_h, u_h)$ if unbounded (without loss of generality, the ill health variable can be similarly defined as $H_{it} = u_h - h_{it}$) (Wagstaff et al., 2003; Erreygers, 2009). The socioeconomic achievement y_{it} for any individual i at period $t = j$, $\forall j \in [1, T]$, can be ranked in ascending order ranging from the least achieved ($r_{it,\ t=j} = 1$) to the most achieved ($r_{it,\ t=j} = n$). The fractional rank R_{it} for period j is defined as $R_{ij} = \frac{1}{n}\left(r_{ij} - \frac{1}{2}\right)$. The relative fractional rank $\overset{\vee}{R}_{ij}$ is defined as $\overset{\vee}{R}_{ij} = \frac{R_{ij}}{\mu_R}$. Since, $\mu_R = \frac{\sum R_{ij}}{n} = \frac{1}{2}$, $\overset{\vee}{R}_{ij} = 2R_{ij}$. Let the relative fractional rank weight z_{it} for period j is defined as $z_{ij} = \overset{\vee}{R}_{ij} - 1$.

Erreygers (2009) showed that the general class of bivariate rank dependent inequality indices for period j can be defined as:

$$I_{t=j}\left(h_{ij}\middle|y_{ij}\right) = f\left(\mu_h^j, l_h, u_h\right)\frac{1}{n}\sum_{i=1,j}^{n} z_{ij}h_{ij} \tag{1}$$

Where, $f(\mu_h^j, l_h, u_h)$ is an index class weighting function (scaling factor). Depending upon how the function is defined, different type of inequality indices will emerge from Eq. (1). For example, the standard concentration index formula for period j (Wagstaff et al., 1991; Kakwani et al., 1997) where, $f(\mu_h^j, l_h, u_h) = \frac{1}{\mu_h^j}$, we have:

$$C_j\left(h_{ij}\middle|y_{ij}\right) = \frac{1}{n\mu_h^j}\sum_{i=1,j}^{n} z_{ij}h_{ij} = \frac{1}{n}\sum_{i=1,j}^{n}\frac{h_{ij}\left(2R_{ij}-1\right)}{\mu_h^j} \tag{2}$$

Similarly, the generalized concentration index (Wagstaff et al., 1991; Clarke et al., 2002), where, $f(\mu_h^j, l_h, u_h) = 1$, we have:

$$V_j\left(h_{ij}\middle|y_{ij}\right) = \frac{1}{n}\sum_{i=1,j}^{n} z_{ij}h_{ij} = \frac{1}{n}\sum_{i=1,j}^{n} h_{ij}\left(2R_{ij}-1\right) \tag{3}$$

or Wagstaff (2005) 's concentration index, where, $f(\mu_h^j, l_h, u_h) = \frac{(u_h - l_h)}{(u_h - \mu_h^j)(\mu_h^j - l_h)}$, we have:

$$W_j\left(h_{ij}\middle|y_{ij}\right) = \frac{(u_h - l_h)}{n\left(u_h - \mu_h^j\right)\left(\mu_h^j - l_h\right)}\sum_{i=1,j}^{n} z_{ij}h_{ij} \tag{4}$$

or Erreygers (2009)'s concentration index, where $f(\mu_h^j, l_h, u_h) = \frac{4}{(u_h - l_h)}$, we have:

$$E_j\left(h_{ij}\middle|y_{ij}\right) = \frac{4}{n(u_h - l_h)}\sum_{i=1,j}^{n} z_{ij}h_{ij} = \frac{4}{n(u_h - l_h)}\sum_{i=1,j}^{n} h_{ij}(2\mathrm{Rij}-1) \tag{5}$$

3.2. Cross-sectional factor decomposition

Wagstaff et al. (2003) in their seminal paper first showed the method for decomposing the standard concentration index. Erreygers and Van Ourti (2011) also showed that Erreygers index can be decomposed into factor contributions in a similar fashion. To explain this, the health outcome determinant function must first be defined. Suppose the health outcome variable at period j can be expressed by the following linear regression equation:

$$h_{ij} = \beta_j + \sum_{k=1}^{q}\beta_{kj}x_{ikj} + \varepsilon_{ij} \tag{6}$$

If we substitute Eq. (6) into Eq. (1) and for notational simplicity define the scaling factor as $f(\mu_h^j, l_h, u_h) = S_{hj}$, then the cross-sectional factor decomposition for all the indices at period j can be expressed as:

$$I_{t=j}^{s}\left(h_{ij}\middle|y_{ij}\right) = S_{hj}\left[\sum_{k=1}^{q}\beta_{kj}S_{kj}^{-1}I_{t=j}^{S}\left(x_{ikj}\middle|y_{ij}\right) + I_{t=j}^{s=V_j}\left(\varepsilon_{ij}\middle|y_{ij}\right)\right] \tag{7}$$

3.3. Longitudinal factor decomposition

Allanson et al. (2010) in their influential work, proposed health and income mobility measures based on the assumption that any change in the standard concentration index over time arises from the combination of change in the individual's health outcomes and their position in the income distribution. They decomposed the difference in the standard concentration index between two periods by adding and subtracting a counterfactual concentration index (CI) measure. The counterfactual CI was constructed such that the health outcome was chosen in the final period, but income was ranked by the initial period. They defined "income-related health mobility" measure as the difference between initial CI and counterfactual CI. Similarly, they defined their "health-related income mobility" measure as the difference between the final CI and the counterfactual CI. Using Erreygers index, Baeten et al. (2013), Coveney et al. (2016), Coveney et al. (2020) showed similar decomposition by either constructing multiple counterfactual CIs using various hypothetical health states (for example, predicted health state with proportionate/ average income growth and no income growth) or changing the ranking criteria by defining various sources of income.

Given a health determinant function in Eq. (6), the hypothetical health state is defined as:

$$\widetilde{h}_{i\tilde{j}} = \widetilde{\beta}_{\tilde{j}} + \sum_{k=1}^{q} \widetilde{\beta}_{k\tilde{j}} \widetilde{x}_{ik\tilde{j}} + \widetilde{\varepsilon}_{i\tilde{j}} \tag{8}$$

For instance, following the formulation of Allanson et al. (2010), $\widetilde{h}_{i\tilde{j}}$ is just the final period health outcome with initial period income ranking (or vice versa). The final period health outcome Eq. (8) becomes:

$$h_{iT} = \beta_T + \sum_{k=1}^{q} \beta_{kT} x_{ikT} + \varepsilon_{iT} \tag{9}$$

Given, Eq. (8) and Eq. (1), a generalised counterfactual CI can be constructed as:

$$\widetilde{I}^{s}_{t=\tilde{j}}\left(\widetilde{h}_{i\tilde{j}} \middle| \widetilde{y}\right) \tag{10}$$

where, for example, the simplest case of $\widetilde{y}$ would be either initial period (y_{i1}) or final period (y_{iT}) income depending upon whether final or initial periods health outcome is chosen. Then the change of socioeconomic health inequality between two periods can be written as:

$$\Delta \mathrm{I}^s(h_{it}|y_{it}) = I^s_{t=T}(h_{iT}|y_{iT}) - I^s_{t=1}(h_{i1}|y_{i1}) \tag{11}$$

Now, if we add and subtract Eq. (10) in Eq. (11) we have:

$$\Delta \mathrm{I}^s(h_{it}|y_{it}) = I^s_{t=T}(h_{iT}|y_{iT}) - \widetilde{I}^s_{t=\tilde{j}}\left(\widetilde{h}_{i\tilde{j}}\middle|\widetilde{y}\right) + \widetilde{I}^s_{t=\tilde{j}}\left(\widetilde{h}_{i\tilde{j}}\middle|\widetilde{y}\right) - I^s_{t=1}(h_{i1}|y_{i1}) \tag{12}$$

Thus, if we chose a counterfactual of final periods health outcome with initial periods income ranking in Eq. (12) we get:

$$\Delta \mathrm{I}^s(h_{it}|y_{it}) = \underbrace{I^s_{t=T}(h_{iT}|y_{iT}) - \widetilde{I}^s_{t=T}(h_{iT}|y_{i1})}_{HRIM} + \underbrace{\widetilde{I}^s_{t=T}(h_{iT}|y_{i1}) - I^s_{t=1}(h_{i1}|y_{i1})}_{IRHM} \tag{13}$$

The HRIM index illustrates the change in socioeconomic inequality resulting from the reshuffling or change in income, while IRHM indicates the shift in socioeconomic inequality due to changes in health independent of any change in income. To understand what factors are driving the HRIM and IRHM, Eq. (13) can be further decomposed. Substituting Eq. (7) in Eq. (13) we get the estimation for longitudinal factor decomposition:

$$\begin{aligned}
\Delta \mathrm{I}^s(h_{it}|y_{it}) \quad = \quad & \underbrace{S_{hT}\left[\sum_{k=1}^{q} \beta_{kT} S^{-1}_{kT} I^s_{t=T}(x_{ikT}|y_{iT})\right] - S_{hT}\left[\sum_{k=1}^{q} \beta_{kT} S^{-1}_{kT} \widetilde{I}^s_{t=\tilde{T}}(x_{ikT}|Y_{i1})\right]}_{Term\ 1\ or\ HRIM} \\
& \underbrace{+ S_{hT}\left[\sum_{k=1}^{q} \beta_{kT} S^{-1}_{kT} \widetilde{I}^s_{t=\tilde{T}}(x_{ikT}|Y_{i1})\right] - S_{h1}\left[\sum_{k=1}^{q} \beta_{k1} S^{-1}_{k1} I^s_{t=1}(x_{ik1}|y_{i1})\right]}_{Term\ 2\ or\ IRHM} \\
& + \underbrace{\left[S_{hT} I^{s=V_T}_{t=T}(\varepsilon_{iT}|y_{iT}) - S_{h1} I^{s=V_1}_{t=1}(\varepsilon_{i1}|y_{i1})\right]}_{residual}
\end{aligned} \tag{14}$$

3.4. The HILDA dataset

This study uses the restricted release version 19 of the Household, Income and Labour Dynamics in Australia (HILDA), a nationally representative, longitudinal survey dataset focusing on social and economic issues. Apart from the general module, which is conducted every year, the survey also includes rotating contents (major modules include: wealth, retirement, health, fertility and education) that are administered every four years. The health module started with wave 9 (in 2009) of the survey and has so far been administered in three waves of the survey (waves 9, 13 and 17). Based on data availability of the variables specified in our model, we use wave 9 and 17 of HILDA data for analysing socioeconomic mental health and income mobility. We constructed a balanced panel of 9277 individuals for analysis. Further, we used longitudinal weights made available by the HILDA to maintain national representativeness. Detailed information about the HILDA survey can be found elsewhere (Summerfield et al., 2019).

3.5. Health outcome measurement

We used mental health as a health outcome for our empirical illustration. A paucity of research on socioeconomic mental health inequality and mobility exists in the literature. We used the Kessler Psychological Distress Scale (K10) to measure mental health outcomes (Kessler et al., 2002). The K10 scale is a widely-used screening tool to monitor mental disorder prevalence and trends globally (Kessler et al., 2009). The score ranges from a minimum score of 10, indicating no distress to a maximum score of 50, referring severe distress (Andrews and Slade, 2001). The scale is used in clinical practice to assess the likelihood of having a mental disorder (Kessler et al., 2003; Wooden, 2009).

3.6. Income measurement

We used equivalised household annual disposable total income as a measure of socioeconomic achievement and rank it in ascending order to construct all our bivariate inequality indices. Detailed information on how the HILDA survey constructs household annual disposable total income can be found elsewhere (Wilkins, 2014; Summerfield et al., 2019). We equivalised the household disposable income variable using the 'modified OECD' equivalence scale formula as follows (ABS, 2006):

$$\ddot{y}_{Hit} = \frac{Y_{Hit}}{1 \times a + 0.5 \times b + 0.3 \times c} \tag{15}$$

Where, $\ddot{y}_{Hit}$= equivalised household annual disposable total income for household H, individual i at period t, Y_{Hit}= household annual disposable total income for household H, individual i at period t, $a = 1$ (first adult), $b =$ number of additional adult members of the household, $c =$ number of child members of the household.

3.7. The mental health determinant function

An individual's mental health is shaped by various social, economic, environmental and demographic factors (Allen et al., 2014). Some determinants of mental health are also shared by physical health, such as, demographic factors like age and gender. However, there are some differences among these factors as well. For example, exposure to life shocks in a person's life course have considerable impacts on mental health (Williams et al., 1981; Hashmi et al., 2020). Further, physical health has an interaction effect on mental health. For instance, studies have found that long term health conditions are associated with mental wellbeing (Cassileth et al., 1984; Scott et al., 2007). Other factors that influence psychological wellbeing are a person's attitude towards risk, their health and social behaviours, specifically smoking/drinking, their community/club or sporting activities and having private health insurance coverage (Lasser et al., 2000; Scott et al., 2007; Doiron et al., 2008). Thus, the mental health determinant function requires careful consideration. In this article, we devise the following reduced form of mental health determinant function:

$$h_{it} = \alpha_t + X_{it}\beta_t + Y_{it}\delta_t + Z_{it}\theta_t + W_{it}\lambda_t + \varepsilon_{it} \tag{16}$$

Where, the dependent variable h_{it} = K10 score (mental health outcome measure), X_{it} = vector of demographic factors, Y_{it} = vector of socioeconomic factors, Z_{it} = vector of behavioural factors, W_{it} = vector of circumstance factors, $\beta,\ \delta, \theta$ *and* λ are parameters to be estimated, α = constant term, ε = residual term, i = individual i and t = period t.

Table 1
Background characteristics.

	2009 (Wave-9)				2017 (Wave-17)			
		Unweighted		Weighted		Unweighted		Weighted
variable description	n	mean	95% ci	mean	n	mean	95% ci	mean
dependent variable								
Kessler 10 score	9277	15.512	(15.386–15.637)	15.738	9277	15.965	(15.829–16.101)	16.262
Demographic factors								
Age								
−15–24 years	1552	0.167	(0.16–0.175)	0.178	316	0.034	(0.031–0.038)	0.043
−25–54 years	5043	0.544	(0.533–0.554)	0.548	4803	0.518	(0.508–0.528)	0.536
−55–64 years	1472	0.159	(0.151–0.166)	0.148	1882	0.196	(0.188–0.205)	0.182
−65+ years	1210	0.13	(0.124–0.137)	0.126	2336	0.252	(0.243–0.261)	0.239
Gender								
-Male	4287	0.462	(0.452–0.472)	0.492	4287	0.462	(0.452–0.472)	0.492
-Female	4990	0.538	(0.528–0.548)	0.508	4990	0.537	(0.528–0.548)	0.508
Socioeconomic status factors								
Education								
-Year 12 or below	4413	0.476	(0.466–0.486)	0.499	3463	0.373	(0.363–0.383)	0.384
-Certificate level	1900	0.205	(0.197–0.213)	0.202	2202	0.237	(0.229–0.246)	0.237
-Undergraduate level	2052	0.221	(0.213–0.23)	0.213	2410	0.26	(0.251–0.269)	0.258
-Post-graduate level	912	0.098	(0.092–0.105)	0.087	1202	0.13	(0.123–0.137)	0.122
Labour force status								
-Employed	6229	0.671	(0.662–0.681)	0.66	5734	0.618	(0.608–0.628)	0.624
-Unemployed	300	0.032	(0.029–0.036)	0.036	205	0.022	(0.019–0.025)	0.025
-Not in the labour force	2748	0.296	(0.287–0.306)	0.304	3338	0.36	(0.35–0.37)	0.351
Behavioural factors								
Covered by private health insurance	5200	0.561	(0.55–0.571)	0.556	5442	0.587	(0.577–0.597)	0.58
Life style: Active membership of club	3341	0.36	(0.35–0.37)	0.339	3312	0.357	(0.347–0.367)	0.335
Life style: Daily smoker	1277	0.138	(0.131–0.145)	0.131	1063	0.115	(0.108–0.121)	0.113
Life style: $\geq$ Drinks 4 standard drinks/day	1452	0.157	(0.149–0.164)	0.149	1243	0.134	(0.127–0.141)	0.136
Circumstance factors								
Have long term health condition	2507	0.27	(0.261–0.279)	0.269	3178	0.343	(0.333–0.352)	0.343
Number of life shocks	9277	0.932	(0.903–0.961)	0.877	9277	0.862	(0.835–0.889)	0.826

3.8. Measurement of covariates

Using the HILDA survey, this study delves into the demographic, socioeconomic, behavioural, and circumstantial factors to the mental health determinant function described above. Demographic factors age (variable: 'hgage') and gender ('hgsex') are considered with age categorised into early working age (15–24 years), prime working age (25–54), peak working age (55–64), and elderly (65+ years). For socioeconomic factors, education level (edhigh1) and labour force status ('esbrd') are assessed. Additionally, private health insurance coverage (phpriin), social engagement through club activities (lsclub), and health behaviour like alcohol consumption (lsdrka) and smoking habits (lssmkf) are investigated. Long-term health conditions are identified through the binary variable 'helth' and a cumulative 'number of life shocks' variable is constructed based on a list of events provided by the HILDA survey (Hashmi et al., 2020). HILDA constructed the long-term condition variable 'helth' by asking the respondent "Looking at SHOWCARD, do you have any long-term health condition, impairment or disability (such as these) that restricts you in your everyday activities, and has lasted or is likely to last, for 6 months or more?". (Further details regarding these life shocks and health conditions can be found in Appendix: Tables A1 and A2).

4. Results

4.1. Sample characteristics

The sample characteristics of the relevant variables included in the analysis for both wave 9 and wave 17 are presented in Table 1. In the baseline wave, young adults (15–24 years of age) account for approximately 17% of the sample. Further, 54.4% of the sample is between the ages of 25 and 54 years old and 55–64 year-olds account for approximately 16% of our sample. The remainder of our sample in wave 9 consists of older aged individuals (aged 65 and up). In wave 17, the sample proportion of young adults (15–24 years of age) is reduced to 3.4%. The sample proportion of 25–54 years old, 55–64 years old and 65+ years old are 51.8%, 19.6% and 25.2% respectively. Approximately 54% of our sample is comprised of females and the rest are males. In wave 9, 20.5% of the sample possessed certificates or diplomas, while 47.6% had education levels of grade 12 or lower. In addition, about 10% of the sample had finished their postgraduate degrees, while 22% had completed undergraduate education. In wave 17, the proportion of higher level of education increased in all levels (year 12 or below: 37.3%, Certificate/diplomas: 23.7%, Undergraduate: 26% and postgraduate: 13%). Over 67% of our sample in wave 9 was employed, while the employment level was lower at 61.8% at wave 17.

The behavioural factors were more or less consistent in both waves (Private health insurance – in wave 9: 56.1% and in wave 17: 58.7%; active club membership in wave 9: 36% and in wave 17: 35.7%; daily smoker in wave 9: 13.8% and in wave 17: 11.0%; Alcohol drinker in wave 9: 15.7% and in wave 17: 13.4%). However, long term health conditions in our sample had increased from 27% in wave 9 to 34.3% in wave 17. Similarly, the mean K10 score also increased from 15.512 in wave 9 to 15.965 in wave 17.

4.2. Trends of socioeconomic mental health inequality in Australia

The trends of income related mental health inequality from 2009 to 2017 in Australia using all five types of rank dependent bivariate inequality indices are presented in Fig. 1. The figure depicts all indices in the negative Y axis domain. This is because the K10 score is an ill health outcome measure and a negative concentration index refers to a pro-poor inequality in ill health outcome, i.e., ill health outcome is concentrated in individuals with low incomes. Initial inspection of Fig. 1 reveals that the generalised

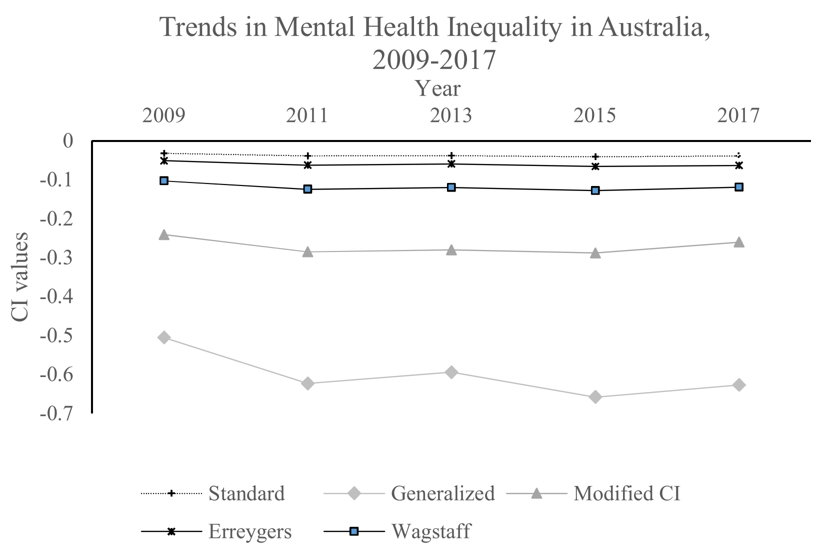

Fig. 1. Trends in five types of concentration indices in Australia, 2009–2017.

concentration index has a declining trend with a cyclical pattern. A similar trend, albeit to a lesser degree can also be seen in the modified concentration index. Other concentration indices show almost a stagnant scenario compared to the generalised concentration index. However, it can be shown that all indices are derived by some form of scaling of the generalised concentration index and thus all indices should follow similar patterns. This will be evident if we just plot two indices instead of five in the same figure. Fig. 2 presents the trends of standard concentration index and Erreygers index. Similar to the pattern of generalised concentration indices in Fig. 1, we observe a cyclical declining trend for standard and Erreygers concentration indices in Fig. 2. The magnitude of changes of the generalised concentration index is masking the changes of all other indices in Fig. 1. In summary, socioeconomic inequality in mental health is gradually worsening in Australia, i.e., the distribution of mental disorder is gradually shifting towards poorer individuals.

4.3. Statistical analysis

We used Stata 15 statistical software for our analysis. To account for survey weights and sample design, we used the SVY command. We used the longitudinal weights (responding person - balanced wave 9 to 17) supplied by HILDA data in our analysis. To estimate all bi-variate rank dependent indices, we used the CONINDEX command (O'Donnell et al., 2016).

To implement the statistical analysis the following steps were followed:

Step 1: To ease the calculation of factor decomposition, we constructed a data matrix and present it in Table 2. Our analysis only illustrates factor decomposition analysis using the standard concentration index (a relative bivariate rank dependent inequality index) and Erreygers index (an absolute bivariate rank dependent inequality index). Because of redundancy, the other rank dependent inequality indices are not illustrated in this study. However, factor decomposition can be analysed using these indices following a similar procedure. Columns (i) and (ii) of Table 2 represent scaling factors of standard CI at period 1 and period T, respectively. Scaling factors of Erreygers index is the same for all periods and it is provided in column (iii). Columns (iv) and (v) present regression coefficients β_k at period T and period 1 respectively. Columns (vi) and (vii) specify factor inequalities using the standard concentration index at period T and period 1 respectively. Columns (viii) and (ix) provide factor inequalities at period T and period 1 using the Erreygers index. Columns (x) and (xi) show counterfactual CIs constructed from standard CI and Erreygers index respectively. We constructed the counterfactual CI by using the final period health outcome with the initial period income ranking. This method of counterfactual construction is chosen because our objective is to analyse health and income mobility.

Step 2: Using Table 2, we estimated the cross-sectional factor decomposition and reported it in Table 3. For example, the factor contribution corresponding to 2009 standard CI in column (i) of Table 3 is derived by multiplying columns (ii), (v) and (vii) of Table 2. Similarly, factor contribution corresponding to 2017 Erreygers index in column (iv) of Table 3 is derived by multiplying column (iii), (iv) and (viii) and so on. The percentage contribution columns are derived from the respective factor contribution column as a percentage of the actual index provided in the last row.

Step 3: Using Table 2, we estimated longitudinal factor decomposition and report it in Table 4. The health-related income mobility (HRIM) of Erreygers index in column (i) of Table 4 is derived by subtracting column (xi) from column (viii) and multiplying the subtracted result subsequently with column (iii) and (iv) of Table 2. The income related health mobility (IRHM) of Erreygers index in column (ii) of Table 4 is derived by first multiplying columns (iii), (iv), (xi) and second, multiplying columns (iii), (v), (ix) in Table 2. Subtracting the later multiplications from the first produces column (ii) of Table 4. Adding columns (i) and (ii) produces column (iii) in Table 4. Similar procedures using standard CI columns in Table 2 produce the decomposition of standard CI in Table 4 (columns iv, v and vi). The Oaxaca-Blinder decomposition (columns vii, viii and ix of Table 4) are also self-explanatory and derived from Table 2.

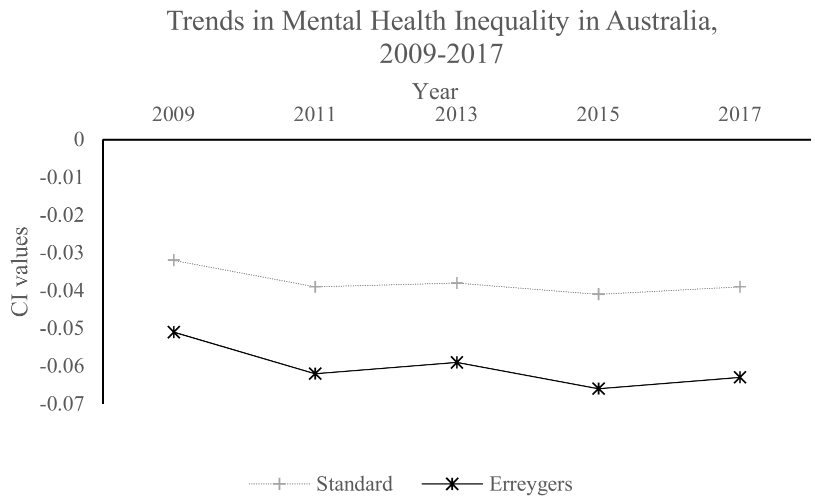

Fig. 2. Trends of standard concentration index and Erreygers index.

Table 2
Data matrix for estimation of factor decomposition analysis[a].

Variables	(i) S^C_{hT}/S^C_{kT}	(ii) S^C_{h1}/S^C_{k1}	(iii) S^E_h/S^E_k	(iv) β_{kT}	(v) β_{k1}	(vi) $I^C_T(x_{ikT}\|y_{iT})$	(vii) $I^C_1(x_{ik1}\|y_{i1})$	(viii) $I^E_T(x_{ikT}\|y_{iT})$	(ix) $I^E_1(x_{ik1}\|y_{i1})$	(x) $\tilde{I}^C(x_{ikT}\|y_{i1})$	(xi) $\tilde{I}^E(x_{ikT}\|y_{i1})$
Age (Ref:15–24 years)											
−25–54 years	0.033	0.035	0.025	−1.987***	−0.836**	0.105	0.085	0.225	0.187	0.057	0.123
−55–64 years	0.011	0.009	0.025	−3.376***	−1.939***	0.097	0.067	0.071	0.04	0.107	0.077
−65+ years	0.015	0.008	0.025	−5.591***	−3.690***	−0.312	−0.397	−0.298	−0.199	−0.191	−0.183
Gender (Ref: Male)											
-Female	0.031	0.032	0.025	0.411*	0.428**	−0.033	−0.027	−0.067	−0.054	−0.027	−0.054
Education (Ref: ≤Year 12)											
-Certificate level	0.015	0.013	0.025	−0.316	−0.305	−0.054	−0.004	−0.051	−0.003	−0.044	−0.041
-Undergraduate level	0.016	0.014	0.025	−0.187	−0.438*	0.181	0.197	0.186	0.168	0.163	0.168
-Post-graduate level	0.008	0.006	0.025	−0.388	−0.192	0.335	0.335	0.163	0.116	0.272	0.132
Labour force status (Ref: Employed)											
-Unemployed	0.002	0.002	0.025	2.37**	1.981***	−0.378	−0.268	−0.038	−0.038	−0.209	−0.021
-Not in the labour force (NLF)	0.022	0.019	0.025	1.357***	1.247***	−0.338	−0.326	−0.473	−0.397	−0.209	−0.293
Covered by private health insurance	0.036	0.035	0.025	−1.073***	−0.896***	0.187	0.19	0.435	0.422	0.18	0.418
Active membership of club	0.021	0.022	0.025	−1.423***	−1.579***	0.046	0.051	0.061	0.07	0.075	0.101
Daily Smoker	0.007	0.008	0.025	1.184*	0.687*	−0.109	−0.109	−0.049	−0.057	−0.157	−0.071
≥ Drinks 4 standard drinks/day	0.008	0.01	0.025	−0.085	0.288	0.077	0.033	0.042	0.02	0.016	0.009
Have long term health condition	0.021	0.017	0.025	3.346***	2.961***	−0.208	−0.201	−0.285	−0.216	−0.175	−0.24
Number of life shocks	0.051	0.056	0.475	0.895***	0.729***	−0.149	−0.131	−0.026	−0.024	−0.132	−0.023
Constant				17.796***	15.916***						

[a] *** $p < 0.001$, ** $p < 0.01$, and * $p < 0.5$.

Table 3
Cross-sectional income related health inequality decomposition for 2009 (Wave-9) and 2017 (Wave-17).

	Factor contributions to CI				% of factor contributions to CI			
	Standard CI		Erreygers		Standard CI		Erreygers	
Variables	(i) 2009	(ii) 2017	(iii) 2009	(iv) 2017	(v) 2009	(vi) 2017	(vii) 2009	(viii) 2017
Age (Ref:15–24 years)								
−25–54 years	−0.003	−0.007	−0.004	−0.011	7.74%	17.84%	7.74%	17.84%
−55–64 years	−0.001	−0.004	−0.002	−0.006	3.81%	9.51%	3.81%	9.51%
−65+ years	0.012	0.026	0.018	0.042	−36.42%	−66.51%	−36.42%	−66.51
Gender (Ref: Male)								
-Female	−0.000	−0.000	−0.001	−0.001	1.14%	1.09%	1.14%	1.09%
Education (Ref: ≤Year 12)								
-Certificate level	0.000	0.000	0.000	0.000	−0.05%	−0.65%	−0.05%	−0.65%
-Undergraduate level	−0.001	−0.001	−0.002	−0.001	3.63%	1.39%	3.63%	1.39%
-Post-graduate level	−0.000	−0.001	−0.001	−0.002	1.10%	2.52%	1.10%	2.52%
Labour force status (Ref: Employed)								
-Unemployed	−0.001	−0.001	−0.002	−0.002	3.75%	3.61%	3.75%	3.61%
-Not in the labour force (NLF)	−0.008	−0.010	−0.012	−0.016	24.5%	25.59%	24.5%	25.59%
Covered by private health insurance	−0.006	−0.007	−0.010	−0.012	18.74%	18.62%	18.74%	18.62%
Active membership of club	−0.002	−0.001	−0.003	−0.002	5.44%	3.47%	5.44%	3.47%
Daily Smoker	−0.001	−0.001	−0.001	−0.002	1.93%	2.33%	1.93%	2.33%
≥ Drink 4 standard drinks/day	0.000	−0.000	0.000	−0.000	−0.28%	0.14%	−0.28%	0.14%
Have long term health condition	−0.010	−0.015	−0.016	−0.024	31.74%	38.1%	31.74%	38.1%
Number of life shocks	−0.005	−0.007	−0.008	−0.011	16.61%	17.54%	16.61%	17.54%
Residual	−0.005	−0.01	−0.008	−0.016	16.62%	25.41%	16.62%	25.41%
Explained	−0.027	−0.029	−0.042	−0.047	83.38%	74.59%	83.38%	74.59%
Actual	−0.032	−0.039	−0.050	−0.063	100.00%	100.00%	100.00%	100.00%

Table 4
Longitudinal decomposition of income related health inequality for 2009 (Wave-9) and 2017 (Wave-17).

	Erreygers			Standard CI (AGP)			Oaxaca-Blinder		
Variables	(i) Term 1 HRIM	(ii) Term 2 IRHM	(iii) T	(iv) Term 1 HRIM	(v) Term 2 IRHM	(vi) T	(vii) Term 1 ΔCE	(viii) Term 2 ΔEC	(ix) T
Age (Ref:15–24 years)									
−25–54 years	−0.0051	−0.0022	−0.0073	−0.0031	−0.0013	−0.0044	−0.0013	−0.0031	−0.0044
−55–64 years	0.0006	−0.0046	−0.0040	0.0004	−0.0028	−0.0024	−0.0011	−0.0013	−0.0024
−65+ years	0.0161	0.0072	0.0233	0.0099	0.0041	0.0139	−0.0070	0.0209	0.0139
Gender (Ref: Male)									
-Female	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Education (Ref: ≤Year 12)									
-Certificate level	0.0001	0.0003	0.0004	0.0000	0.0002	0.0002	0.0002	0.0000	0.0002
-Undergraduate level	−0.0001	0.0010	0.0010	−0.0001	0.0007	0.0006	0.0000	0.0006	0.0006
-Post-graduate level	−0.0003	−0.0007	−0.0010	−0.0002	−0.0004	−0.0006	0.0000	−0.0006	−0.0006
Labour force status (Ref: Employed)									
-Unemployed	−0.0010	0.0006	−0.0004	−0.0006	0.0004	−0.0002	−0.0004	0.0002	−0.0002
-Not in the labour force (NLF)	−0.0061	0.0024	−0.0037	−0.0038	0.0018	−0.0020	−0.0003	−0.0017	−0.0020
Covered by private health insurance	−0.0004	−0.0018	−0.0022	−0.0003	−0.0009	−0.0012	0.0001	−0.0013	−0.0012
Active membership of club	0.0014	−0.0008	0.0006	0.0009	−0.0005	0.0004	0.0002	0.0002	0.0004
Daily Smoker	0.0006	−0.0011	−0.0005	0.0004	−0.0007	−0.0003	0.0000	−0.0003	−0.0003
≥Drink 4 standard drinks/day	−0.0001	−0.0002	−0.0002	0.0000	−0.0001	−0.0001	0.0000	−0.0001	−0.0001
Have long term health condition	−0.0038	−0.0040	−0.0078	−0.0023	−0.0022	−0.0045	−0.0005	−0.0040	−0.0045
Number of life shocks	−0.0012	−0.0014	−0.0026	−0.0007	−0.0007	−0.0014	−0.0008	−0.0006	−0.0014
Total explained	0.0005	−0.0052	−0.0046	0.0003	−0.0023	−0.0020	−0.0110	0.0090	−0.0020
Residual	−0.0057	−0.0018	−0.0075	−0.0035	−0.0010	−0.0045	−0.0076	0.0031	−0.0045
Actual	−0.0052	−0.0070	−0.0122	−0.0032	−0.0033	−0.0065	−0.0185	0.0121	−0.0065
% Explained	−10.61%	73.92%	38.15%	−10.61%	70.95%	30.90%	59.23%	74.35%	30.90%

4.4. *Cross-sectional decomposition of socioeconomic mental health inequality*

The estimates of cross-sectional factor contributions and their respective percentages to standard CIs and Erreygers indices for year 2009 and 2017 are reported in Table 3. The model explains socioeconomic mental health inequality of approximately 83% and 75% in 2009 and 2017, respectively. Factor contribution to socioeconomic inequality can arise from two different sources. The first is the regression coefficients of the health determinant function, and the second is the socioeconomic inequality of the factor itself.

Understanding this relationship has important implications in our analysis. For example, education level contributes to socioeconomic inequality in mental health by 4.68% (certificate: −0.05%, undergraduate: 3.63% and post-graduate 1.1%) and 3.26% (certificate:−0.65%, undergraduate: 1.39% and post-graduate 2.52%) respectively in 2009 and 2017. However, if we inspect the regression coefficients of columns (iv) and (v) in Table 2, we see that, except for undergraduate education in 2009, all coefficients are insignificant. Thus, inspecting the factor inequalities columns (columns vi-ix) in Table 2 reveals that, education contribution to socioeconomic inequality of mental health in Table 3 is coming from socioeconomic inequalities in education. In summary, our results suggest that, while education level may not be significant in the mental health determinant function, there is socioeconomic inequality in education. The variation in education levels due to income disparities serves as a source of socioeconomic inequality in mental health. This type of inequality is structural in nature, implying that addressing it may be challenging when rooted in such structural disparities.

If both the regression coefficient and socioeconomic factor inequality are substantial, the factor contribution will be large. However, if either or both sources are low, the factor contribution will be small. Thus, a larger factor contribution implies a greater impact from both sources. Table 3 reports that the major factor contributors are long term health conditions (31.74% and 38.1% in 2009 and 2017, respectively), not in the labour force (NLF) (24.5% and 25.59% in 2009 and 2017, respectively), private health insurance (18.74% and 18.62% in 2009 and 2017, respectively) and frequency of life shocks (16.61% and 17.54% in 2009 and 2017, respectively). All of these factors have significant regression coefficients. Table 2 shows that long term health conditions increase the K10 score (i.e., reduces mental health) and also have a pro-poor distribution (i.e., more poor than rich people have long term conditions). Similar effects are also observed for NLF and frequency of life shocks. In the case of private health insurance coverage, the regression coefficient reduces the K10 score (improves mental health) and the factor distribution is pro-rich (positive values). Thus, these factors add large negative values to concentration indices, i.e., higher K10 scores are distributed more in the poorer segments of society (more psychological distress and higher concentration of mental disorders).

The mental health behaviour variables add minor contributions to the socioeconomic mental health inequality. For example, Table 2 reports that club and sporting activity reduces K10 scores and has a pro-rich distribution (Table 3 reports 5.44% and 3.47% respectively in 2009 and 2017). Similarly, smoking also increases K10 scores and has a pro-poor distribution (Table 3 reports 1.93% and 2.33% respectively in 2009 and 2017). Alcohol consumption does not have significant regression coefficients and does not contribute to socioeconomic mental health inequality in our estimates. Being female also has minor contribution to socioeconomic mental health inequality (Table 3 reports 1.14% and 1.09% respectively in 2009 and 2017). However, the demographic factor, age, makes a large contribution to socioeconomic mental health inequality (Table 3). Table 2 reports regression coefficients that are more negative in higher age groups. The working age groups (age 25–54 and 55–64) have pro-rich socioeconomic inequality and the retirement age group (65+ years) has pro-poor socioeconomic inequality. Thus, being of retirement age increases pro-rich inequality and reduces pro-poor socioeconomic inequality by a large margin.

4.5. *Longitudinal decomposition of socioeconomic mental health inequality*

Table 4 presents the longitudinal decomposition analysis of socioeconomic mental health inequality. In this analysis, we constructed our counterfactual socioeconomic inequality index using the final period's (wave 17, year 2017) health outcome with the initial period's income ranking (wave 9, year 2009). The first column shows factor contributions of health-related income mobility (HRIM) (term 1 of Eq. (14)). Since, the health outcome is fixed in this column and the income ranking is changing between the periods, this column shows the effect of income reshuffling. The next column shows factor contributions of income-related health mobility (IRHM) (term 2 of Eq. (14)). The income ranking is fixed with initial ranking in this column, so that the factor contributions of health outcome change are reflected here. This allows us to determine whether health changes are progressive (regressive) in favour of poor (rich), which is of principal interest in this paper. The third column is derived by adding the first two columns and thus depicts the total changes contributed by the factor. The first three columns are derived using the Erreygers index (an absolute concentration index). A similar exercise is reported in the next three columns also using standard concentration index (a relative concentration index) for comparing normative value judgments. Finally, the last three columns report the Oaxaca-Blinder decomposition for comparison purpose. A careful inspection reveals that the factor contributions of total changes in the Oaxaca-Blinder decomposition (last column) is exactly the same as the factor contribution of total changes in the standard concentration index (column vi). However, the HRIM and IRHM are different.

Our model performs well in understanding IRHM as it explains approximately 74% and 71% of the contributions in Erreygers and standard concentration indexes, respectively. The major factors that negatively affect the poor in the health mobility index are long term health conditions, private health insurance coverage and number of life shocks (−0.004, −0.0018 and −0.0014 respectively in the Erreygers index, and −0.0022, −0.0009 and −0.0007 respectively in the standard CI). Poorer individuals' circumstances play a major role in mental health mobility. Health behaviour such as smoking, drinking and club membership plays a relatively smaller role. The major factor that positively affect the poor in IRHM are labour force status and retirement age. Since, Australia is a welfare state country, benefits at retirement age have a positive impact for society. Better economic conditions also have positive impacts on the poor's mental health.

The HRIM effects for labour force status are much stronger than the IRHM effects. The stronger negative effect in HRIM counteracts the weaker positive effects in IRHM, resulting in a net negative effect from labour force status during this period. The overall changes in factor contribution are explained by 38% and 31% respectively for Erreygers and standard concentration indices. Similar to the cross-sectional analysis, factors such as long-term health conditions, number of life shocks, and NLF are the major drivers of the changes of socioeconomic inequality in mental health. There was no change in socioeconomic inequality for females. Socioeconomic inequality in female mental health is thus structural in nature. The Oaxaca-Blinder decomposition also revealed that long term health conditions, private insurance and NLF contributes to socioeconomic inequality through the change in elasticities.

5. Discussion

This study investigated key factors associated with socioeconomic inequality in mental health and outlined the dynamics influencing the evolution of such inequalities. The results indicate that adverse circumstantial factors such as long-term health conditions, exposure to life shocks, unfavourable labour force status and lack of private health insurance coverage are the primary contributor to socioeconomic inequality in mental health. Additionally, the study highlights that, these same factors act as the major drivers of mental health inequality.

Our study adds strong evidence to the growing body of research highlighting the key factors driving socioeconomic inequalities in mental health. Consistent with findings with studies across the globe in diverse contexts (Lee and Jones, 2007; Morasae et al., 2012; Gunasekara et al., 2013; Mutyambizi et al., 2019; León-Giraldo et al., 2021; Srivastava et al., 2021), we confirm factors like long-term health conditions, unfavourable labour force status, and life shock events are major contributors to these disparities. Additionally, our study complements findings by Linder et al. (2020) suggesting that education might not be the primary factor contributing this inequality.

A key strength of this paper lies in its innovative analysis of income and health mobility's contributions to socioeconomic inequality in mental health. Our findings reveal that factors such as long-term health conditions, life shocks, and private health insurance coverage exacerbate these disparities through a complex interplay of both health-related income mobility (HRIM) and income related health mobility indices (IRHM). Notably, IRHM emerges as the more potent driver of inequality than HRIM in the above-mentioned factors highlighting the need for policy interventions that prioritise health in their strategies. Interestingly, for labour force changes, while mental health is slightly positive for the poorest (progressive IRHM, i.e., poorer suffer a smaller share of health loss), the income effect outweighs it, making the overall impact regressive. This shows income changes due to changes in the labour force status led to greater health losses for the poor than the direct health benefits of those shifts. Furthermore, our findings reveal a pro-rich bias in the accessibility of private health insurance in Australia, as poorer individuals have less access to these benefits. In Australia, despite some subsidized specialist care options through better access scheme, the limited capacity of the program further aggravates mental health inequality.

In summary, circumstantial factors are the major driving force of socioeconomic mental health inequality. To account for this, Australian governments can optimize healthcare resources and address mental health inequality by investing in cost-effective intervention strategies for vulnerable groups. This could involve increase investments in a comprehensive prevention and early intervention service program, with a focus on technology-enabled integrated care, online parenting support, family education and culturally appropriate care. This would optimize healthcare resources while tackling the social factors that contribute to mental health disparities

6. Conclusions

Health inequalities due to a citizens' socioeconomic position are unfair. Social and economic conditions define individuals' health opportunities and thereby determine their risk of illness. On equity grounds, most developed and developing countries thus want to reduce such inequalities so that people have equal opportunities regardless of their socio-economic status. Understanding the measurement and examination of the key sources that drives socioeconomic health inequalities overtime is thus essential to design policy interventions aimed at their reduction. This paper contributes empirical findings to the literature on socioeconomic health inequality.

We analyse the sources and recent intensification of socioeconomic mental health inequality in Australia. Using HILDA longitudinal survey data from waves 9 and 17, we deduce that factors like long term health conditions and life shock exposure are the major drivers of socioeconomic mental health inequality. Socioeconomic factors such as labour force status, and behavioural factors such as private health insurance and community/club activities also play a significant role in determining individual outcomes. Our analysis also reveals that the older age group contributes to a large reduction in socioeconomic mental health inequality. Our hypothesis in this regard is that elderly people create a positive externality by reducing socioeconomic mental health inequality. Future research has the potential to examine the effect of ageing on socioeconomic mental health inequality.

A specific limitation of this study that warrants acknowledgment is its non-causal inference design. Albeit strong theoretical underpinning, the methodology primarily involves an accounting exercise, and caution is necessary in interpreting the study's findings. Despite these limitations, the study offers valuable insights into factors associated with mental health inequality. Additionally, awareness is required regarding potential measurement error and recall bias associated with study variables derived from the HILDA survey. Nevertheless, the impact of such errors is minimised given the large sample size. Future research avenues may focus on methodological advancements in causal inference in socioeconomic inequality.

Appendix

Table A1
List of life shock variables used to determine number of life-shocks.

Sl	Variable name	Life shock description
1	lesep	Separated from spouse
2	leins	Serious personal injury/illness
3	leinf	Serious injury/illness to family member
4	ledsc	Death of spouse or child
5	ledrl	Death of close relative/family member
6	ledfr	Death of a close friend
7	levio	Victim of physical violence
8	lepcm	Victim of a property crime
9	lejls	Detained in jail
10	lejlf	Close family member detained in jail
11	lefrd	Fired or made redundant
12	ledhm	A weather related disaster (flood, bushfire, cyclone) damaged or destroyed home
13	fiprbeg	Unable to pay electricity, gas or telephone bills on time
14	fiprbmr	Unable to pay mortgage or rent on time
15	fiprbps	Pawned or sold something
16	fiprbwm	Went without meals
17	fiprbuh	Was unable to heat home
18	fiprbfh	Asked for financial help from friends or family
19	fiprbwo	Asked for help from welfare/community organisations

Table A2
List of long-term conditions.

Sl	Long term condition
1	Sight problems not corrected by glasses or lenses
2	Hearing problems
3	Speech problems
4	Blackouts, fits or loss of consciousness
5	Difficulty learning or understanding things
6	Limited use of arms or fingers
7	Difficulty gripping things
8	Limited use of feet or legs
9	A nervous or emotional condition which requires treatment
10	Any condition that restricts physical activity or physical work (e.g., back problems, migraines)
11	Any disfigurement or deformity
12	Any mental illness which requires help or supervision
13	Shortness of breath or difficulty breathing
14	Chronic or recurring pain
15	Long-term effects as a result of a head injury, stroke or other brain damage
16	A long-term condition or ailment which is still restrictive even though it is being treated or medication is being taken for it
17	Any other long-term condition such as arthritis, asthma, heart disease, Alzheimer's disease, dementia, etc.

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