An investigation of body mass distributional changes in Australia, 1995–2017/18

Anushiya Vijayasivajie*, Pundarik Mukhopadhyaya, Chris Heaton

Economics Department, Macquarie University, Macquarie University, 4-6 Eastern Road, NSW 2109, Australia

ARTICLE INFO

Keywords:
Body Mass Index
Waist-to-Height Ratio
Inequality
Generalised Entropy Index
Relative Distributions
Polarisation

ABSTRACT

This study investigates changes in the distribution of body mass for adult Australians between 1995 and 2017/18. Using three nationally representative health surveys, we first apply the parametric generalised entropy (GE) class of inequality indices to measure the level of disparity in the body mass distribution. Results from the GE measure reveal that, while growth of body mass inequality is a population-wide experience, demographic and socio-economic factors explain only a modest portion of total inequality. We then apply the relative distributions (RD) method to garner richer insights on changes to the body mass distribution. The non-parametric RD method reveals growth in the proportion of adult Australians falling into the upper deciles of the body mass distribution since 1995. Then, hypothetically keeping the shape of the distribution unchanged, we discern that body mass increases across all deciles of the distribution (location effect) is an important contributor to the observed distributional change. After removing the location effect, however, we find a non-trivial role for distributional shape changes (growth of the proportion of adults at the upper and lower parts of the distribution as the proportion in the middle diminish). While our findings support current policy directions that target the population as a whole, factors driving shape changes to the body mass distribution also need consideration when designing anti-obesity campaigns, especially when aimed at women.

1. Introduction

Obesity, or unhealthy body mass, has reached “epidemic” levels across many developed and developing countries in recent times (World Health Organization, 2021), and Australia is no exception. In 2017/18, one in three adult Australians were obese (Australian Bureau of Statistics, 2018). In fact, the rate of prevalence of obesity has risen markedly since 1995; from 19% to 31% (Australian Institute of Health and Welfare, 2020). The situation is troubling to medical practitioners and policymakers because obesity impacts a wide range of areas. From a health standpoint, obesity is a risk factor for many conditions, such as cardiovascular diseases (Aune et al., 2017; Hagg et al., 2015), type 2 diabetes (Freemantle et al., 2008; Golay and Ybarra, 2005), depressive disorders (Carpenter et al., 2000; De Wit et al., 2010), etc. On the other hand, the consequences of unhealthy body mass can spill into the labour and/or marriage markets. For instance, there is ample evidence of inequalities in the labour market linked to individuals’ body mass.

Specifically, studies discern an obesity wage penalty (Brunello and D’Hombres, 2007; Cawley, 2004; Han et al., 2009; Johar and Katayama, 2012), or non-hiring/longer spells of unemployment of obese individuals (Caliendo and Lee, 2013; Tunceli et al., 2006). There are also growing obesity-related costs that have a major impact on the economy. In Australia, the direct and indirect costs of obesity totalled $3.7 billion in 2005, rising to $8.2 billion in 2008 (Access Economics, 2008).

In investigating obesity in Australia, most empirical studies have implemented regression-based methods. As such, they examine the conditional mean or probability relationship between certain characteristics (socio-economic status, lifestyle behaviours, etc.) and body mass (Brennan et al., 2009; Cameron et al., 2003; Gearon et al., 2015; Giles-Corti et al., 2003; Keating et al., 2015). However, looking beyond the regression approach in a study of the full body mass distribution is advantageous. For example, examining the entire distribution is insightful because it utilizes all distributional information. Thus, as part of the analytic process, important shape changes to the distribution are

---

* Corresponding author.

E-mail address: anushiya.vijayasivajie@mq.edu.au (A. Vijayasivajie).

1 Body mass index (BMI) is the most commonly used measure to discern the categories of overweight and obese. BMI is calculated as the ratio of an individual’s weight (in kilograms) to the individual’s height (in metres) squared (WHO, 2000). BMI < 18.5 kg/m² implies underweight; 18.5 kg/m² ≤ BMI < 25 kg/m² implies normal weight; 25 kg/m² ≤ BMI < 30 kg/m² implies overweight; BMI ≥ 30 kg/m² implies obese.

https://doi.org/10.1016/j.ehb.2023.101270

Received 9 January 2023; Received in revised form 22 June 2023; Accepted 26 June 2023

Available online 1 July 2023

1570-677X/© 2023 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).
picked the distributional approach also supports a different perspective; to discern distribution-centred effects rather than social/individual processes as the source underlying body mass changes. Accordingly, the drivers of change are identified in the specifics of changes to the body mass distribution: shifting of the entire distribution (showing the increase/decrease in the body mass of the entire population) and/or distributional shape changes (showing specific groups’ gain/loss of body mass).

Since inequality is a property of the distribution, it also deserves dedicated investigation. Specifically, given that body mass is an indicator of health, inequality of body mass reveals useful information on inequalities in health and longevity. On a broader level, however, body mass is an indicator of wellbeing; encapsulating health, literacy, access to (food and non-food) resources, among other things (Sahn, 2009; Sahn and Younger, 2009). Therefore, measuring inequality of body mass provides a good picture of the extent of inequality in multi-dimensional wellbeing.

To date only two studies, Peeters et al. (2015) and Walls et al. (2010), have used distributional methods to examine changes of body mass in Australia. While the studies reveal growing right-tail skewness of the general body mass distribution since 1980, the implemented methods—Tukey mean-difference plot (Walls et al., 2010) and quantile regression (Peeters et al., 2015)—do not support richer analyses. In particular, it is not possible to investigate the sources of the changes. Also, other than assessing the skewness of the distribution, it is not possible to conduct finer probes into distributional shape changes. In this study, we build on the previous (two) studies by focussing on the specifics and sources of distributional density and inequality change of body mass in Australia between 1995 and 2017/18.

To examine the distributional aspects of body mass, we employ two methods: inequality indices and relative distributions (RD). Besides telling the story of body mass changes in Australia from two distinct distributional perspectives—parametric absolute distribution (inequality indices) and non-parametric comparative distribution (RD)—along with other advantages, our methods facilitate deeper analysis into the factors that drive the change. In particular, inequality indices are univariate (summary) measures that quantify the extent of deviation from perfect equality of an outcome in the population (Hao and Naiman, 2010). Hence, they reveal the magnitude of absolute disparity in the distribution of body mass. While inequality indices possess specific properties that facilitate further analyses, they are distribution-sensitive indices (i.e., responsive to differences across the distribution). Thus, we rely on several indices of the generalised entropy (GE) class to detect differences at certain parts of the body mass distribution. Further, since the GE class is additively decomposable (into between and within subgroups), we are then able to evaluate the role of demographic and socio-economic characteristics in explaining total inequality of body mass. The RD method, on the other hand, offers an integrated framework for evaluating comparative distributional changes. Besides generating visual displays on density changes to the body mass distribution, RD provides insights into the sources driving the changes (Handcock and Morris, 1998, 1999). As such, we can determine whether the rising incidence of obesity in Australia is attributable to the entire population gaining body mass (location shift) and/or specific (distributional) sub-population groups gaining body mass (shape shift). Additionally, the RD-based polarisation indices offer a fuller picture on the shape changes to the body mass distribution. Extending beyond distributional skewness, the polarisation indices disclose information on the size of density movement from the median to the upper and/or lower tails, or the converse. Thus, we are able to discern the proportion of adults of normal weight shifting to the underweight and/or obese range over time.

Employing inequality indices and the RD method, we extend the prevailing narrative on changes to the body mass distribution in Australia. Along the way, we address the two main limitations of past Australia-based (distributional) studies. In particular, given that Walls et al. (2010) and Peeters et al. (2015) compromise on inter-temporal comparability by relying on several (methodologically) different surveys, we instead employ three nationally representative datasets from the same survey type, the National Health Survey. Additionally, unlike Walls et al. (2010) and Peeters et al. (2015), our analyses capture the entire adult population of Australia, not just the sub-population of urban-residing Australian adults. Finally, to get a robust picture of body mass change in Australia, we employ BMI and waist-to-height ratio (WHR), a measure of general and central body mass, respectively, in all our analyses.

Our study makes several valuable contributions to the literature in Australia. First, we widen the existing (regression- and distribution-based) knowledge on obesity to reveal the specifics and sources of distributional density and inequality change in Australia. This task is made possible by the use of our novel (to the Australian context) distributional tools of inequality indices and RD. In particular, the RD method is able to shed light, both graphically and non-graphically, on the distribution-level sources driving body mass changes. Additionally, the RD-polarisation analyses of our study are the first attempt at revealing the size and nature of the shape change to the body mass distribution in Australia, and their effects on vulnerable groups. Third, besides capturing the total adult population (not just city-dwellers) of Australia, our analysis of body mass distributional changes extends the time horizon to the most recent survey year of 2017/18. Lastly, our decision to employ two distinct measures of body mass (BMI and WHR) yields a broader perspective on the changes to the body mass distribution in Australia. This is an important feature of our study because the earlier works of Walls et al. (2010) and Peeters et al. (2015) have relied solely on BMI. However, there is ample evidence that general (BMI) and central (WHR) measures of body mass have different health risk profiles (Ho et al., 2003; Lee et al., 2008; Schneider et al., 2010). In general, going beyond the scope of prior studies, we are able to provide a more up-to-date and nuanced picture about the changes to the (general and central) body mass distribution in Australia between 1995 and 2017.

The rest of the paper is structured as follows. In Section 2, we present a survey of the studies that use distributional methods to investigate body-mass changes in a range of countries. Section 3 details our data sources and other related information. Section 4 provides a short summary on inequality indices and the RD method. Section 5 details and discusses the results of our analyses. Finally, Section 6 summarises our main findings and concludes with some policy implications.

growth of inequality of (general) body mass (in women) across several developing countries. On the other hand, using a range of inequality indices, Pak et al. (2016) document rises in inequality of (general) body mass in the United States (US) between 1971 and 2014. Analysing further, they discern that within-group inequality is the primary contributor, accounting for up to 95% of total inequality of body mass. Analogous results are also observed in China (Nie et al., 2019) and Cuba (Nie et al., 2021). Specifically, while inequality of (general) body mass rose by 14% in China between 1991 and 2011, and in Cuba by 4.6% between 2001 and 2010, within-group inequality is responsible for at least 84% of total inequality in both countries.

In addition to inequality indices, some studies have also implemented other distributional tools, such as stochastic dominance, growth incidence curves (GICs) and the RD method, to investigate body mass changes. For example, using stochastic dominance, Pak et al. (2016) and Nie et al. (2019) reveal changes to the distribution of (general) body mass in the US and China, respectively; in contrast, Madden (2012) fails to find any significant change to the distribution of (general) body mass in Ireland between 2002 and 2007. The GICs shed more light on the observed distributional changes: at the upper tails of the body mass distribution, a growth rate higher than the mean prevails. Quite surprisingly, these patterns of body mass distributional change are also noted among women in developing countries (Sahn, 2009).

The RD method, on the other hand, has mainly been used to examine distributional changes in income (Bernhardt et al., 1995; Clementi et al., 2017; Morris et al., 1994; Petrarca and Ricciuti, 2016). However, breaking this trend, Contoyannis and Wildman (2007) and Houle (2010) apply it to study distributional changes of body mass. Based on the RD method, Contoyannis and Wildman (2007) show that, while there has been significant density growth (between 1994 and 2001) at the upper parts of the (general) body mass distribution in England, polarisation (shape effect) is an important driver of this change. Meanwhile, Houle (2010) reveals (general) body mass polarisation along racial and educational lines in the US between 1999 and 2006. Specifically, for men, there is a growth of the proportion of “least-educated” to “most-educated” adults at both distributional tails; for women, this density growth occurs only at the upper part of the distribution.

3. Data

For this study, data are sourced from three surveys undertaken by the Australian Bureau of Statistics (ABS): the National Nutrition Survey 1995 (NNS 1995); the National Health Survey 2007/08 (NHS 2007/08); and the National Health Survey 2017/18 (NHS 2017/18). The NNS 1995 is related to the National Health Survey 1995 (NHS 1995) as it uses a select sub-sample of the NHS 1995. We do not use the NHS 1995 because measurements of body mass are self-reported by participants of this survey. The NNS 1995 and NHS series are cross-sectional surveys based on stratified multi-stage sampling of urban and rural dwellings (households) in all states and territories of Australia. While the NHS series comprise of a random sample of one adult (18 years old or over) and one child (0–17 years old) per household, the NNS 1995 comprises of a random sample of two in-scope persons per urban household, and three in-scope persons per rural household. All surveys involve face-to-face interviews conducted by trained interviewers. More survey details are presented in Supplementary Appendix 1. In analysing body mass changes, our main interest lies in the entire period, 1995–2017. We also comment, however, on the sub-time periods, 1995–2007 (early period) and 2007–2017 (recent period). Our final sample is restricted to adults 18 years old and above, and excludes pregnant women. In accordance with ABS recommendations, sampling weights are applied (in all our analyses) to generate estimates that are representative of the in-scope population in Australia for the survey year.4

3.1. Measures of body mass

In this study, we employ two measures of body mass: BMI and WHtR, measured as follows:

\[
BMI = \frac{\text{Body weight (in kilograms)}}{\left(\text{Height (in metres)}\right)^2}
\]

\[
WHtR = \frac{\text{Waist circumference (in cm)}}{\text{Height (in cm)}}
\]

The use of two different measures of body mass is helpful for several reasons. Firstly, while BMI is an indicator of general body mass, WHtR reflects central (or abdominal) body mass. Thus, they offer an all-encompassing picture of body mass changes in Australia by revealing whether the pattern of distributional change differs across general and central measures of body mass. Secondly, the use of WHtR counters the main criticism levelled at BMI—it is a crude index that does not distinguish between body fat and body muscle (Prentice and Jebb, 2001; Rothman, 2008). As a result, BMI is not sensitive to body mass compositional changes that occur with age. In fact, it is possible for individuals to maintain the same BMI even though there are changes in the ratio of body fat to muscle as they age. Thirdly, compared to BMI and other measures of central body mass, WHtR is a better indicator of unhealthy body mass as it has been found to be more strongly linked to certain physical diseases (Ashwell et al., 2012; Browning et al., 2010; Schneider et al., 2010). Also, the use of WHtR reduces data heaping (i.e., rounding of the data to the nearest whole number or nearest one decimal point). Therefore, we are able to obtain more precise RD estimates. Additionally, the height, body weight and waist circumference (WC) data used to calculate BMI and WHtR are objective measures collected by trained interviewers.5 Hence, the risks of self-reporting biases (underestimation of body weight and WC, and overestimation of height) are removed. Finally, we recode body weight greater than 140 kg as 140 kg to maintain inter-temporal comparison since the maximum recordings of the weighing scales have changed since 1995.6

3.2. Demographic and socio-economic characteristics

We also assess body mass changes by sub-population groups defined

---

4 Our study has two main limitations that require some discussion. Firstly, due to the non-availability of an imputation identifier in ABS’s Basic Confidentialised Unit Record Files (CURF) datasets, we do not conduct any sensitivity analysis accounting for imputed body mass values in the NHS 2017. It is not clear if this leads to underestimation or overestimation, although we suspect underestimation is more likely. Secondly, there may be further underestimation due to the truncation applied to (general) body mass values at the upper end.

5 WC data are not available as part of the Basic CURF dataset of NHS 2007.

6 In this respect, we follow the study of Gearon et al. (2015) which also truncates body weight data to allow for inter-temporal comparisons. In the NNS 1995 and NHS 2007, the weighing scale measured up to a maximum of 139.9 kg and 150 kg, respectively. In the NHS 2017, the maximum recording is 200 kg. Moreover, in the Basic CURF dataset of the NHS 2007, height and weight are provided in a truncated form: truncation of height of less than 145 cm and greater than 200 cm; truncation of weight of less than 40 kg and greater than 140 kg. We do not to truncate height and weight at the lower end because we want to retain as much of the original data as possible for our analysis of the entire period.
on the basis of demographic and socio-economic characteristics. Demographic sub-population groups are identified using (i) gender (men and women) and (ii) age (young-age, middle-age, and old-age); socio-economic sub-population groups are identified using (i) educational attainment (high-education and low-education) and (ii) household income (low-household income, medium-household income, and high-household income). In some analyses, we use combinations of these characteristics. Supplementary Appendix 2 provides details on these sub-population groups. While all data (of our final sample) are available for the demographic characteristics, this is not so for the socio-economic characteristics due to non-responses, non-collection of data, etc. Overall, the number of missing observations is small; 2–14% of the total final sample. The only exception, however, is for educational attainment in 1995, where out of the total sample of 10652 observations, only 5135 observations are available for analysis.\footnote{In this paper, gender captures the biological or physiological characteristics of persons.}

4. Methodology

4.1. Inequality indices

To measure body mass inequality in Australia, we apply the GE class of univariate indices. Even though there are several classes of indices (i.e., Gini, Atkinson, etc.) that can be utilised, we choose the GE class because it has a flexible form (see below) that identifies specific parts (lower or upper) of the distribution characterised by greater or lesser inequality (Cowell, 2011; Hao and Naiman, 2010).

For the demographic characteristics, this is not so for the socio-economic characteristics due to non-responses, non-collection of data, etc. Overall, the number of missing observations is small; 2–14% of the total final sample. The only exception, however, is for educational attainment in 1995, where out of the total sample of 10652 observations, only 5135 observations are available for analysis.\footnote{We conduct t-tests of the null hypotheses of equal expected values of BMI and WHtR for those with and without educational attainment information. The results indicate that there are no statistically significant differences in expected BMI or WHtR between the two groups (refer to Supplementary Appendix 3).}

\[
GE(\alpha) = \begin{cases} 
\sum_{j=1}^{m} \left( \frac{Y_j}{\sum_j Y_j} \right)^{1-\alpha} \frac{N_j}{N} \cdot GE(\alpha) + \frac{1}{a(a-1)} \sum_{j=1}^{m} N_j \left[ \frac{Y_j}{\sum_j Y_j} \right]^{1-\alpha}, & \alpha \neq 0, 1 \\
\sum_{j=1}^{m} N_j \cdot GE(\alpha) + \sum_{j=1}^{m} N_j \ln \left( \frac{Y_j}{\sum_j Y_j} \right) a = 0 & \\
\sum_{j=1}^{m} N_j \cdot GE(\alpha) + \sum_{j=1}^{m} N_j \ln \left( \frac{Y_j}{\sum_j Y_j} \right) a = 1 & \end{cases} 
\]

GE(\alpha) = \begin{cases} 
\frac{1}{N(a-1)} \sum_{i=1}^{N} \left[ \frac{Y_i}{\sum_j Y_j} \right]^{a} - 1, & \alpha \neq 0, 1 \\
-\frac{1}{N} \sum_{i=1}^{N} \ln \left( \frac{Y_i}{\sum_j Y_j} \right), & a = 0 \\
\frac{1}{N} \sum_{i=1}^{N} Y_i \ln \left( \frac{Y_i}{\sum_j Y_j} \right), & a = 1 
\end{cases} \quad (1)

N is the total number of persons in the population; \( \bar{Y} \) is the mean of the body mass measure; \( Y_i \) is body mass measure of individual \( i \). Another reason for selecting the GE class is because it possesses the desirable properties of anonymity, population principle, scale invariance and additive decomposability.\footnote{Population principle, scale invariance and additive decomposability ensure that the values of the GE indices remain invariant to replications of the population of interest and the use of other related body mass measures, respectively. Specifically, scale invariance implies that it does not matter if body mass is measured using weight (not BMI) and waist circumference (not WHR). Anonymity ensures that only the characteristic of interest (in this case, the body mass of individuals) is considered in the calculation of \( GE(\alpha) \). In particular, anonymity ensures that if two males and two females report a general body mass difference of 1 kg/m\(^2\), each gender group contributes equally to the GE index value. Finally, since the transfer principle is concerned about equity, it ensures that the \( GE(\alpha) \) value decreases when the situation of an obese person improves (i.e., loses a certain amount of body mass), while the converse is observed in a non-obese person (they experience a gain in body mass of the same amount).}

While our second analysis sheds light on the role of demographic and socio-economic characteristics in explaining total inequality (if within-group inequality is less (more) than between-group inequality, we can conclude that the grouping characteristic explains (does not explain) the observed total body mass inequality), a similar conclusion cannot be made based on the first analysis; in the first analysis, the specific characteristic does not explain total inequality in a population to inequality within and between sub-population groups. From the GE class indices, we select \( GE(0), GE(1) \) and \( GE(2) \). These indices are obtained by setting \( \alpha \) (a sensitivity parameter) to 0, 1 and 2. Since \( \alpha \) assigns specific weights to differences between body mass levels at different parts of distribution, GE(0), GE(1) and GE(2) assign more weight to differences at the lower part, middle part and upper part of the distribution, respectively. Due to our interest in obesity (upper-tail), we consider GE(2) as our base index. Meanwhile, besides divulging the extent of inequality at the other parts of the distribution, GE(0) and G(1) provide validation on the robustness of our results. The GE values range between 0 and 1; a GE value of 0 represents perfect equality of body mass (every adult in Australia has the same body mass), and higher values capture the extent of deviation from the situation of perfect equality.

4.1.1. Sub-population group analyses

To garner more insights about the changes to body mass inequality in Australia, we conduct (two more) demographic and socio-economic sub-population group-based analyses. In the first analysis, we measure the magnitude of body mass inequality and its growth in the sub-population groups. In the second analysis, we decompose total inequality into within-group and between-group inequality.\footnote{While our second analysis sheds light on the role of demographic and socio-economic characteristics in explaining total inequality (if within-group inequality is less (more) than between-group inequality, we can conclude that the grouping characteristic explains (does not explain) the observed total body mass inequality), a similar conclusion cannot be made based on the first analysis; in the first analysis, the specific characteristic does not explain total inequality in a population to inequality within and between sub-population groups. From the GE class indices, we select \( GE(0), GE(1) \) and \( GE(2) \). These indices are obtained by setting \( \alpha \) (a sensitivity parameter) to 0, 1 and 2. Since \( \alpha \) assigns specific weights to differences between body mass levels at different parts of distribution, GE(0), GE(1) and GE(2) assign more weight to differences at the lower part, middle part and upper part of the distribution, respectively. Due to our interest in obesity (upper-tail), we consider GE(2) as our base index. Meanwhile, besides divulging the extent of inequality at the other parts of the distribution, GE(0) and G(1) provide validation on the robustness of our results. The GE values range between 0 and 1; a GE value of 0 represents perfect equality of body mass (every adult in Australia has the same body mass), and higher values capture the extent of deviation from the situation of perfect equality.}

The within-group and between-group components of the GE class are as follows:

\[
\text{Within-Group} \quad \text{Between-Group} \\
\sum_{j=1}^{m} N_j GE(\alpha) + \sum_{j=1}^{m} N_j \ln \left( \frac{Y_j}{\sum_j Y_j} \right) a = 0 \\
\sum_{j=1}^{m} N_j GE(\alpha) + \sum_{j=1}^{m} N_j \ln \left( \frac{Y_j}{\sum_j Y_j} \right) a = 1
\]
GE(α) denotes the GE index value of sub-population group j; N_j represents the number of individuals in sub-population group j; N represents the total number of individuals in the population; Y_j is the mean body mass of sub-population group j; Y denotes the mean body mass of the total population.

4.2. Relative distributions

Unlike inequality indices, the RD method offers an integrated non-parametric framework that facilitates direct comparative distributional analysis. Firstly, there are graphical displays that reveal the specifics of density changes to the body mass distribution. Then its decompositions probe into the sources driving the changes. There are also summary measures that complement the graphical displays by quantifying key features of the distributional changes. In this section, we detail some aspects of the RD method.

4.2.1. Relative probability density function

The RD method compares the distributions of a single variable (i.e., income, body-mass, etc.) in two (cross-sectional or across-time) populations (Handcock and Morris, 1998, 1999). But unlike inequality indices, it probes into distributional differences directly via transforming the two (population) distributions into a single distribution. Consider our (continuous) body-mass variable denoted as Y_0 in 1995, and its cumulative density function (CDF) is F_0(y). Y_1 is the body mass variable in 2017, and its CDF is F_1(y). Accordingly, Y_0 and Y_1 are our reference and comparison populations, respectively. The RD is the transformation of Y_1 by the CDF of Y_0 which generates the random variable, R.

\[ R = F_0(Y_1), \quad r \in [0, 1] \]  

(3)

While R measures the relative rank of Y_1 compared to Y_0, it is continuous on the outcome space [0,1] and its realisations, known as “relative data” are denoted as r. As a random variable, R has a cumulative distribution function (CDF) and a probability density function (PDF). Since the PDF of R, referred to as relative PDF (or relative density) and denoted as g(r), is a proper density that integrates to 1 over the unit interval, it forms the basis for the development of other analyses. In terms of understanding the relative PDF, it represents the density of the relative distribution to the density of the reference distribution at a given r, as follows:

Relative PDF : \( g(r) = \frac{f_Y(Y_1)}{f_Y(Y_1)} = \frac{f_Y(y_1)}{f_Y(y_1)} \) \( 0 \leq r \leq 1, y_1 \geq 0 \)  

(4)

where \( f_Y \) denotes the density function of Y_1; \( f_Y \) denotes the density function of Y_0; \( F_Y^{-1}(r) = y_1 \) is the quantile function of Y_0. Interpreting the relative PDF is straightforward; since it is a rescaled density ratio of the comparison to reference distribution, if there are no distributional changes of body mass since 1995, then the relative PDF reveals a horizontal line at g(r)=1. Conversely, if there is density growth (reduction) at specific quantiles of the body mass distribution, then g(r) is above (below) 1 at those quantiles.

4.2.2. Source decomposition

Besides divulging details on body mass distributional change, the relative PDF can also shed light on the sources driving the changes: location and/or shape effects. In our study, these effects identify whether the entire adult population is gaining or losing an extra constant amount of body mass (location effect) and/or specific (distributional) sub-populations are gaining or losing extra body mass (shape effect). The source decomposition proceeds with the generation of a counterfactual distribution, Y_C, where Y_C is the additive median (or mean) location-adjusted reference distribution, and its density is \( f_Y \)  

Specifically, Y_C is constructed by adding the difference between the medians of the comparison and reference distribution to every observation of the reference distribution: \( Y_C = Y_0 + \rho, \) where \( \rho = \text{median } Y_1 - \text{median } Y_0. \) Using these three distributions, we can then disentangle the location and shape effect from the (total) relative PDF, as follows:

\[ g(r) = \frac{f_Y(Y_1)}{f_Y(Y_0)} = \frac{f_Y(Y_1)}{f_Y(Y_0)} \times \frac{f_Y(Y_0)}{f_Y(Y_0)} \]  

(5)

The relative PDF of \( \frac{f_Y(y)}{f_Y(y)} \) captures the location effect, that is, the movement of the entire body mass distribution holding the distributional shape constant. Accordingly, if the entire 2017 adult population has gained (lost) a constant amount of body mass since 1995, then the resultant graph will reveal a monotonic incline (decline). The relative PDF of \( \frac{f_Y(y)}{f_Y(y)} \) on the other hand, captures the shape effect net of the location effect. Specifically, it captures all shape-related distributional changes, including spread, skewness, etc., holding the distributional location constant. In terms of the resultant graphs, the shape effect can reveal two distinct types of patterns: 1) polarisation (shift of mass from the distributional centre to the lower- and upper-tails) indicated by a U-shape; or 2) convergence (shift of mass from the distributional tails to the centre) indicated by an inverted U-shape.

4.2.3. Kullback-Leibler divergence measures

While the graphical displays are an integral part of the RD method, the relative PDFs can also be employed to generate (two sets of) summary measures that add precision to the graphs. Unlike other summary measures, the RD-based summary indices are robust to the presence of outliers and deviation from assumptions. The first set of summary statistics are based on the entropy index, Kullback-Leibler (KL) divergence, and complements the graphical displays by quantifying the magnitude of the total distributional change and their sources. Specifically, the entropy measure \( D(F_1;F_0) \) quantifies the total entropy (total distributional change) between the 2017 and 1995 distribution, and the other entropies, \( D(F_1;F_C) \) and \( D(F_C;F_0) \) quantify the location and shape effect, respectively.

\[ D(F_1;F_0) = \int_{-\infty}^{\infty} \log \left( \frac{f_Y(y)}{f_Y(y)} \right) df_Y(y) = \int_{0}^{1} \log(g(r))g(r)dr \]  

(6)

4.2.4. Relative polarisation indices

The other set of RD-based summary statistics offers precise details on the shape effect by quantifying the magnitude of polarisation or convergence; it does so by making use of the median relative polarisation (MRP) index. Based on a median location-adjusted RD \( g(r) \), MRP measures mean absolute deviation around \( g(r) \), rescaled to ensure that it ranges between –1 and 1, and weighted by \( |r - \frac{1}{2}| \) to emphasise the deviations in the tails, as follows:

\[ \text{MRP} \left( F_1;F_0 \right) = 4 \int_{0}^{1} r \left( \frac{1}{2} g(r) \right) dr - 1 \]  

(7)

Positive and negative MRP values indicate polarisation and convergence, respectively. No polarisation or convergence is indicated by 0. The MRP value is interpretable as the proportional shift of mass from the distributional centre to the less central (lower and upper) parts. Therefore, if MRP = 0.292, this implies that 29.2% of the population mass shifted from the middle to the upper and/or lower parts of the
distribution. Further, given that MRP is additively decomposable, we can ascertain the specifics of polarisation: the magnitude of upper-tail and lower-tail polarisation. To this end, the relative polarisation indices of lower relative polarisation (LRP) and upper relative polarisation (URP) are used. Like the MRP values, the values of LRP and URP can ascertain the specifics of polarisation: the magnitude of upper-tail and lower-tail polarisation. To this end, the relative polarisation indices of lower relative polarisation (LRP) and upper relative polarisation (URP) are used. Like the MRP values, the values of LRP and URP also range between 1 and 1, with 0 indicating no lower- or upper-tail polarisation. The additive decomposability of MRP implies that MRP = \frac{1}{2} \text{LRP} + \frac{1}{2} \text{URP}.

\text{LRP} = \int_{0}^{1} \left( 1 - \frac{1}{2} \phi(r) \right) dr - 1 \tag{8}

\text{URP} = \int_{0}^{1} \left( - \frac{1}{2} \phi(r) \right) dr - 1 \tag{9}

5. Results and discussion

5.1. Preliminary results: summary statistics and kernel density graphs

General and central body mass summary statistics are presented in Table 1.12 The results reveal rises (1% level of significance) in mean and median body mass between 1995 and 2017, with median general body mass increasing by 5.5%, and median central body mass up by 7.0%. In terms of the sub-time periods, we note that the growth of median (general) body mass in the recent period (3.1%) exceeds the growth in the early period (2.4%). As a precursor to our main distributional analyses, we then examine the kernel density (KD) graphs of the body mass measures in Supplementary Appendix 6. The KD graphs indicate the occurrence of two forms of distributional change in Australia between 1995 and 2017: a rightward shift of the entire body mass distribution, and distributional density (shape) changes. On the first phenomena, while it is characterised by the modal point moving to higher body mass values, it appears more pronounced for central than general body mass. The distributional shape change, on the other hand, appears to take a distinct form. Specifically, there is upper-tail density growth as the distributional centre hollows out. Thus, at the expense of the distributional peak lowering, there is more mass at/above the (general) obesity threshold of 30 kg/m² in 2017 than in 1995. We observe similar patterns of results in our sub-time periods for general body mass, and also in our gender-specific KD graphs.

5.2. Body mass inequality

GE-based estimates of body mass inequality are presented in Table 2. The results disclose an increase (1% level of significance) in inequality of body mass in Australia between 1995 and 2017. While general body mass inequality is always greater than central body mass inequality, its growth is also (nearly two-fold) larger. Based on GE(2), inequality of general body mass rose by 29% (0.016–0.021), and inequality of central body mass grew by 17% (0.012–0.014). The other GE indices, G(0) and G(1), also reveal inequality rises of similar magnitudes. Our results align with studies (Choi et al., 2018; Lee et al., 2008; Schneider et al., 2010) that document distinct health risk profiles for general and central body mass. In particular, WHtR is revealed as a far superior predictor of cardiovascular risks than BMI. Nevertheless, we note a strong correlation of around 0.8 between BMI and WHtR in our study (Supplementary Appendix 5). Furthermore, there is more inequality at the upper part of the body mass distribution as GE(2) consistently shows the largest index values. Focussing on the sub-time periods, we observe that growth of (general) body mass inequality in the early period surpasses the growth in the recent period. Specifically, based on GE(2), inequality of (general) body mass grew by 17% (0.016–0.019) and 10% (0.019–0.021) in the early and recent period, respectively.

In general, our results for Australia are consistent with past studies that also report growth of inequality of body mass in other countries (Nie et al., 2019; Nie et al., 2021; Pak et al., 2016). On the other hand, given that body mass is also an indicator of material well-being, our estimates of body mass inequality are lower than estimates of income inequality in Australia. For instance, Greenville et al. (2013) discern estimates of income inequality of 0.31–0.43 (Gini-based) between 1988/89 and 2009/10 in Australia, and our Gini-based estimates of body mass inequality (not presented for the sake of brevity) range between 0.09876 (in 1995) and 0.11307 (in 2017). Additionally, even though, our

---

Note: With the exception of the number of observations, all estimates are calculated using sampling weights. In the Mean and Median columns, the jackknife or linearised (for 1995) standard error is presented in parenthesis. In the Mean Change and Median Change columns, the percentage change between the survey years is presented in parenthesis. * denotes p < 0.1, ** denotes p < 0.05 and *** denotes p < 0.01.

---

<table>
<thead>
<tr>
<th>Survey Year</th>
<th>No. of Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Mean Change (Level &amp; %)</th>
<th>Median Change (Level &amp; %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>10,652</td>
<td>0.036</td>
<td>0.036</td>
<td>0.036</td>
<td>(2.73%) (0.00149)</td>
<td>(2.39%) (0.00126)</td>
</tr>
<tr>
<td>2007</td>
<td>10,982</td>
<td>0.036</td>
<td>0.036</td>
<td>0.036</td>
<td>(3.66%) (0.00119)</td>
<td>(3.06%) (0.00117)</td>
</tr>
<tr>
<td>2017</td>
<td>16,305</td>
<td>0.036</td>
<td>0.036</td>
<td>0.036</td>
<td>(4.68%) (0.00119)</td>
<td>(5.53%) (0.00120)</td>
</tr>
<tr>
<td>Entire Period</td>
<td></td>
<td>0.036</td>
<td>0.036</td>
<td>0.036</td>
<td>(7.03%) (0.00149)</td>
<td>(7.03%) (0.00126)</td>
</tr>
</tbody>
</table>

**Table 1** Summary Statistics—Full Sample.13

<table>
<thead>
<tr>
<th>Survey Year</th>
<th>No. of Obs.</th>
<th>Mean</th>
<th>Median</th>
<th>Std. Dev.</th>
<th>Mean Change (Level &amp; %)</th>
<th>Median Change (Level &amp; %)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>10,639</td>
<td>0.5180</td>
<td>0.5091</td>
<td>0.00102</td>
<td>(0.00092) (0.00126)</td>
<td>(0.00102) (0.00126)</td>
</tr>
<tr>
<td>2007</td>
<td>10,982</td>
<td>0.5180</td>
<td>0.5091</td>
<td>0.00102</td>
<td>(0.00126) (0.00126)</td>
<td>(0.00126) (0.00126)</td>
</tr>
<tr>
<td>2017</td>
<td>16,305</td>
<td>0.5180</td>
<td>0.5091</td>
<td>0.00102</td>
<td>(0.00126) (0.00126)</td>
<td>(0.00126) (0.00126)</td>
</tr>
<tr>
<td>Entire Period</td>
<td></td>
<td>0.5180</td>
<td>0.5091</td>
<td>0.00102</td>
<td>(0.00126) (0.00126)</td>
<td>(0.00126) (0.00126)</td>
</tr>
</tbody>
</table>

**Table 2** Summary Statistics—Full Sample.

---

12 Prevalence rates of the categories of body mass (overweight, obese, etc.) are detailed in Supplementary Appendix 4. Our estimates of overweight, obese, etc. match estimates provided by other sources (AIHW2020; Obesity Evidence Hub, 2021).

13 For the 2007 and 2017 survey years, jackknife standard errors using ABS provided replicate weights (and sampling weights) are calculated; they correct for the complex survey design of the NHS 2007 and NHS 2017. On the other hand, since no replicate weights are provided as part of the NNS 1995, linearised standard errors are calculated using only sampling weights.
observed GE index values are small, they are almost comparable to other estimates of health inequality. Specifically, Nie et al. (2019) document GE(2)-based estimates of body mass inequality of 0.0069–0.0108 in China; whereas, focussing on physical healthy days, Sehili et al. (2005) uncover much higher estimates of 0.035–0.041 in the US.

Taking the next step, we analyse body mass inequality by demographic and socio-economic characteristics. The GE(2)-based inequality change results are detailed in Table 3. Several aspects stand out from this analysis. First, aligning with our previous (full sample) results, inequality of body mass rose (1% level of significance) in most sub-population groups between 1995 and 2017. Second, while the growth of inequality is larger for general body mass than central body mass across all sub-population groups, inequality is almost always greater at the upper than lower part of the distribution. Finally, regardless of the body mass measure, inequality is consistently higher in certain demographic (women and young-age) and socio-economic (low-education and low-household income) groups.

On the demographic characteristics, although inequality of (general and central) body mass is higher in women and the young-age groups, the larger growths are experienced by men and the old-age groups. We find a similar pattern of results in the socio-economic groups. Even though inequality of body mass is higher in the low-education and low-household income groups, growth of inequality is greater in the high-education and high-household income groups. Our results contrast starkly with the findings of Nie et al. (2019) for China, where the young and low socio-economic groups experience the largest inequality growth. The results for the sub-time period, on the other hand, mirror the (full sample) results in Table 2. Thus, across most sub-population groups, the larger (general) body mass inequality growth rate is observed in the early rather than the recent period. The exceptions, however, are the old-age and low-household income groups. In the old-age group, inequality of general body mass grew by 24% and 11% in the recent and early period, respectively; it rose by 17% (recent period) and 2% (early period) in the low-household income group.

The sub-population analysis results provide strong evidence that the growth of inequality of body mass in Australia between 1995 and 2017 is a population-wide experience occurring across all demographic and socio-economic groups. To ascertain whether demographic and socio-economic factors explain total inequality, we decompose total body mass inequality into within- and between-group inequality as in Eq. 2. The GE(2)-based decomposition results are detailed in Supplementary Appendix 9. We find that demographic and socio-economic characteristics explain little of the total inequality of body mass in Australia. Our conclusion is based on the high share, 83–99%, attributable to within-group inequality in each survey year. On the other hand, we also observe a distinct disparity of results (between general and central body mass) for the age characteristic. Specifically, while our estimates of the contribution of age to inequality of general body mass is minimal (up to 4%), its contribution to inequality of central body mass is substantially greater (13–17%). This result, however, is consistent with the evidence (Prentice and Jebb, 2001; Rothman, 2008) that BMI does not pick up important age-related changes (i.e., individuals tend to gain body fat and lose body muscle as they age). Unsurprisingly, the high within-group inequality share persists even as combinations of characteristics are considered. Thus, we find that the combination of gender, age, and education explains only 23% (at most) of total central body mass inequality, and 7% of general body mass inequality. Our findings concur with the broader literature for body mass (Nie et al., 2019; Nie et al., 2021) and general health (Asada, 2005; Pradhan et al., 2003; Sehili et al., 2005). For example, Nie et al. (2019) disclose within-group estimates of 84–90% for general body mass, and 79–83% for central (WC) body mass; and Pradhan et al.’s (2003) cross-country study reveals a within-group share of more than two thirds of total world health inequality among young children.

Note: Sampling weights are applied. Jackknife or linearised (for 1995 & entire period) standard errors are presented in parentheses. * denotes p < 0.1, ** denotes p < 0.05 and *** denotes p < 0.01.

Table 2

<table>
<thead>
<tr>
<th>Body Mass Index (BMI)</th>
<th>Sensitivity Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survey Year</td>
<td>G (2) Level Change</td>
</tr>
<tr>
<td>1995</td>
<td>0.01644</td>
</tr>
<tr>
<td>2007</td>
<td>0.01922</td>
</tr>
<tr>
<td>2017</td>
<td>0.02121</td>
</tr>
<tr>
<td>Entire Period</td>
<td>0.04777 **</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Waist-to-Height Ratio (WHtR)</th>
<th>Sensitivity Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Survey Year</td>
<td>G (2) Level Change</td>
</tr>
<tr>
<td>1995</td>
<td>0.01198</td>
</tr>
<tr>
<td>2007</td>
<td>0.01400</td>
</tr>
<tr>
<td>Entire Period</td>
<td>0.00202 **</td>
</tr>
</tbody>
</table>

15 Detailed GE(0)- and GE(1)-based decomposition results are presented in Supplementary Appendix 10. Again, our substantive conclusions still hold across the different indices.

14 The actual values of GE(2), as well as GE(0) and GE(1), by demographic and socio-economic characteristics in each survey year are presented in Supplementary Appendix 7. The inequality change results based on GE(0) and GE(1) are detailed in Supplementary Appendix 8. Despite the slight differences in the GE(0), GE(1) and GE(2) results, most of our substantive conclusions still hold.
Table 3: Body Mass Inequality Changes By Demographic and Socio-Economic Sub-Population Groups—Based on GED(2)

<table>
<thead>
<tr>
<th>Gender</th>
<th>Age</th>
<th>Education</th>
<th>Household Income</th>
<th>Body Mass Index (BMI)</th>
<th>Entire Period</th>
<th>Early Period</th>
<th>Recent Period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Low-HI Income</td>
<td>Medium-HI Income</td>
<td>High-HI Income</td>
<td>(34.80%)</td>
<td>(24.93%)</td>
<td>(30.62%)</td>
</tr>
<tr>
<td>Men</td>
<td>Young Age</td>
<td>0.00439 **</td>
<td>0.00393 **</td>
<td>0.00346 **</td>
<td>(0.9)</td>
<td>(0.8)</td>
<td>(0.9)</td>
</tr>
<tr>
<td></td>
<td>Middle Age</td>
<td>0.00419 **</td>
<td>0.00372 **</td>
<td>0.00329 **</td>
<td>(1.0)</td>
<td>(1.0)</td>
<td>(1.0)</td>
</tr>
<tr>
<td></td>
<td>Old Age</td>
<td>0.00399 **</td>
<td>0.00357 **</td>
<td>0.00312 **</td>
<td>(0.9)</td>
<td>(0.9)</td>
<td>(0.9)</td>
</tr>
<tr>
<td>Women</td>
<td>Young Age</td>
<td>0.00399 **</td>
<td>0.00357 **</td>
<td>0.00312 **</td>
<td>(1.0)</td>
<td>(1.0)</td>
<td>(1.0)</td>
</tr>
<tr>
<td></td>
<td>Middle Age</td>
<td>0.00419 **</td>
<td>0.00372 **</td>
<td>0.00329 **</td>
<td>(1.0)</td>
<td>(1.0)</td>
<td>(1.0)</td>
</tr>
<tr>
<td></td>
<td>Old Age</td>
<td>0.00399 **</td>
<td>0.00357 **</td>
<td>0.00312 **</td>
<td>(1.0)</td>
<td>(1.0)</td>
<td>(1.0)</td>
</tr>
</tbody>
</table>

Note: Sampling weights are applied. The percentage change in body mass inequality in the different time periods are detailed in parentheses. * denotes p < 0.1, ** denotes p < 0.05 and *** denotes p < 0.01.

5.3 Relative distributions

5.3.1 Overall

To get a different distributional perspective on body mass changes in Australia, we now implement the RD method.16 The relative PDFs in Fig. 1 show clear distributional changes since 1995, with more density in the 2017 than the 1995 cohort at the upper deciles (r ≥ 0.5) of the body mass distributions.17 Interestingly, unlike our results on inequality of body mass, there is no marked difference in the relative PDFs of general and central body mass. The result highlights that a greater proportion of Australian adults in 2017 (compared to 1995) fall into the clinically high risk ranges of overweight and obese. The largest distributional difference, however, is observed at the uppermost 9th decile, at which the 2017 cohort has a density roughly 1.5–2.5 times that of the 1995 cohort. In contrast, the largest over-representation by the 1995 cohort is found at the lowest deciles of the body mass distribution. Even though, in the sub-time periods, density growth at the uppermost decile is smaller (only 1.5 times more), it is comparable to the estimates obtained by Contoyannis and Wildman (2007) for England over a similar time period (between 1994 and 2001).

To garner information on the sources driving the changes, we decompose total distributional change into the location and shape effects as in Eq. 5. The graphical display results are presented in Fig. 2. The first graph on the relative density of Yc to Y0 discloses a sizeable location shift, characterised by greater density in the 2017 than 1995 cohort starting at the 4th decile of the 1995 (reference) distribution. We note, however, that the distributional tails in Fig. 1 are not well produced by this location shift. For instance, while the relative density at the top (r > 0.9) and bottom deciles (r < 0.1) of the general body mass distribution in Fig. 2 are about 0.5 and 1.5, respectively, they are below the 0.8 and 2.5 observed in Fig. 1. This observation suggests that some of the disparity at the distributional tails is due to the shape effect.

The relative density of Y1 to Yc (second graph) confirms our conjecture that the shape effect plays a non-trivial role in affecting body mass distributional changes in Australia between 1995 and 2017. In particular, the shape effect appears to take the form of polarisation—density growth at the lower (r < 0.1) and upper (r > 0.8) deciles at the expense of the distributional middle hollowing out. Interestingly, although the location effect appears to prevail over the shape effect for central body mass (as the relative PDF curve is steep and the U-shape is less defined), for general body mass, both effects appear equally prominent. Considering the sub-time periods, our decomposition graphs suggest that, although both the location and shape effects matter, their magnitudes are greatly diminished. Also, it is difficult to ascertain the more dominant effect in each sub-time period.

We then rely on the KL divergence results in Table 4 to add precision to...
the graphical insights. The KL divergence estimates are sensitive to the specifics of the computation of the underlying relative density (Jann, 2021). In particular, it is possible to obtain estimates using kernel density or histogram of the relative density. Our (main) estimates shown in Table 4 are based on the histogram of the relative density. The results show that both effects have contributed to drive distributional changes of body mass in Australia between 1995 and 2017. Confirming our earlier observations, while the location effect is the more powerful force driving distributional change of central body mass, both effects are equally potent for general body mass change. Our results are consistent with the recent findings of Peeters et al. (2015); besides shape changes to the general body mass distribution in Australia, they also report mean growth across the percentiles of the distribution. In relation to other countries, Nie et al. (2019) also reach similar conclusions. Specifically, using Kakwani decomposition, mean-growth effect (similar to the location effect in RD) as revealed as the main contributor to central (and general) body mass distributional change in China. Additionally, our results (Supplementary Appendix 15) also suggest that the dominance of the location effect has in fact risen between the sub-time periods; in the early period, it accounts for about 17% (not statistically significant) of the total general body mass distributional change, and this increases to 54% in the recent period.

Despite the (often) secondary role of the shape effect, it still explains a non-trivial portion of total body mass distributional changes in Australia between 1995 and 2017. Therefore, we now turn to the MRP, LRP and URP indices for more information on the shape effect. The results in Table 5 confirm that, while there has been polarisation, the magnitude of polarisation is greater for general (12%) than for central (7.8%) body mass. There are also distinct patterns of polarisation for the two measures of body mass; just slightly more (6.8% out of 12%) moved from the median to the upper-tail of the general body mass distribution, and marginally more (4.5% out of 7.8%) shifted to the lower-tail of the central body mass distribution. Our findings about the nuances of the shape change to the body mass distribution in Australia are, to our knowledge, new. While Peeters et al. (2015) and Walls et al. (2010) disclose growing upper-tail skewness of the general body mass distribution in Australia since 1980, our results extend this distributional picture. Accordingly, we reveal that the shape change of the body mass distribution in Australia is far more encompassing, characterised by density growth at the lower- and upper-tails as the central density shrinks.

### 5.3.2. Based on demographic and socio-economic characteristics

While the previous relative PDFs disclose the specifics of body mass distributional changes, they do not account for demographic and socio-economic compositional changes in the Australian population over time, and their effects on the distribution of body mass. In fact, Supplementary Appendix 16 shows clear demographic and socio-economic (covariate) compositional changes in Australia between 1995 and 2017. Specifically, there is a greater proportion of women and old-age persons in 2017 than 1995; there are also more persons from a high-education and middle-household income backgrounds in 2017 than 1995. Demographic and socio-economic compositional changes are likewise evident in the sub-time periods. Thus, in the forthcoming set of analyses, we employ the RD method to each sub-population group to directly

---

**Fig. 1. Relative PDF—Full Sample.** Note: Sampling weights are applied.

---

18 The relative PDF curve is indicated by the solid blue line. The upper and lower limits of the 95% confidence interval (of the relative PDF curve) are indicated by the shaded area. The red horizontal line at $g(r) = 1$ represents the line of distributional density parity (i.e., no body mass distributional density change between the survey years). On the other hand, if there is density growth at specific quantiles, then $g(r) > 1$ at those quantiles; if there is density reduction at specific quantiles, then $g(r) < 1$ at those quantiles. Also, the scale at the top of the relative PDF diagram is based on units of persons. Hence, the distance between BMI of 25 kg/m$^2$ and 30 kg/m$^2$ is larger than the distance between 30 kg/m$^2$ and 35 kg/m$^2$ because more individuals fall into the first than the second range.

19 We present the histogram-based estimates as our main results since they align closely to the MRP results. For example, among men, the histogram-based results (unlike the kernel density-based results) reveal that the shape effect for central body mass is statistically significant, and this is consistent with the MRP results. In Supplementary Appendix 13 and 14, we detail estimates based on the kernel density of the relative density.

20 While the precise estimate values based on the kernel density of the relative density are different to our main histogram-based results, the substantive conclusions remain unchanged for central body-mass. On the other hand, we are unable to conclusively determine the stronger effect driving distributional changes of general body mass.

21 The polarisation indices are symmetric (Handcock and Morris, 1998; Hao and Naiman, 2010). Hence, it does not matter if the reference and comparison populations are swapped; switching the populations generates indices of the same magnitude but opposite sign.
remove the undesired impact of covariate compositional changes.\textsuperscript{23} Besides checking the robustness (or otherwise) of our earlier results, the new analyses offer richer insights into the nature of body mass distributional changes within sub-population groups.

5.3.2.1. By demographic characteristics. The relative PDFs of all demographic sub-population groups are presented in Fig. 3. Analogous to our (full sample) results in Fig. 1, the relative PDFs show density growth at the upper deciles of the body mass distribution in all gender and age groups. Hence, it is clear that demographic change is not major force driving distributional changes of body mass in Australia since holding the demographic characteristics constant does not substantially change the relative PDFs. Investigating the sources of the change, Fig. 4 shows that both effects are implicated as there is a distinct incline and U-shape in the respective graphs. Focussing on the shape effect in the gender groups, we observe a more marked upper-tail polarisation in men, while lower-tail polarisation is more pronounced in women. The results of the sub-time periods, on the other hand, echo our earlier full sample results. Thus, there are comparatively muted patterns of density changes at the uppermost decile in the demographic groups (Supplementary Appendix 19).

Furthermore, the entropy results shown in Table 4 indicate that, the location effect consistently overwhelms the shape effect in men, though most prominently for central than general body mass. The shape effect, however, always dominates in women (83\% and 52\% of general and central body mass distributional changes, respectively). This pattern of results is also noted in the sub-time periods (Supplementary Appendix 15). In particular, the shape effect accounts for about 116\% and 72\% of the distributional change of general body mass in women in both sub-time periods; the location effect (66\%) prevails in men in the recent period. Our results match the past findings of Walls et al. (2010) and Peeters et al. (2015) as they discern a greater increase in the skewness of the (general) body mass distribution of Australian women than men. Employing the RD method, Contoyannis and Wildman (2007) also document a similar pattern of results in England. Specifically, (general) body mass distributional change in women is mainly due to the shape effect, while the location effect is the primary driver of distributional change in men. Across our age groups, in contrast, we observe an almost consistent dominance of the location effect (58\%–71\%) for central body mass; it is only 28\%–37\% for general body mass.

On the specifics of the shape effect across the demographic groups, Table 5 reveals that, in women, a larger share of about 9\% (out of a mass shift of 14.8\%) and 10\% (out of a mass shift of 15.7\%) moved from the median to the lower part of the general and central body mass distributions, respectively. Meanwhile, in men, most of the mass (8.3\% out of a mass move of 11\%) shifted to the upper part of the general body mass distribution. Although our findings on the specifics of the shape effect in women are consistent with Walls et al.’s (2010) study, it adds a new

\textsuperscript{23} This method is referred to as “categorical contrasts” by Handcock and Morris (1998). The RD framework also offers another method of analysis (covariate adjusted RD) to isolate the impact of demographic and socio-economic changes on the distribution of body mass. We provide a short description of this method (Supplementary Appendix 17), and then present the associated results in Supplementary Appendix 18. The findings using this method align with our forthcoming results based on categorical contrasts.
### Table 4

<table>
<thead>
<tr>
<th>Body Mass Index (BMI)</th>
<th>Location Effect</th>
<th>Shape Effect</th>
<th>Location Effect Share</th>
<th>Shape Effect Share</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total (KL)</strong></td>
<td>0.06218 ** **</td>
<td>0.02793 ** **</td>
<td>0.03424 ** **</td>
<td>44.93%</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td>(0.00571)</td>
<td>(0.00434)</td>
<td>(0.00435)</td>
<td></td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td>0.06375 ** **</td>
<td>0.01080 ** **</td>
<td>0.05295 ** **</td>
<td>16.94%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00650)</td>
<td>(0.00540)</td>
<td>(0.00714)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td>0.08191 ** **</td>
<td>0.04887 ** **</td>
<td>0.03304 ** **</td>
<td>59.66%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00776)</td>
<td>(0.00593)</td>
<td>(0.00472)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Young-Age</strong></td>
<td>0.05184 ** **</td>
<td>0.01462 ** **</td>
<td>0.03722 ** **</td>
<td>28.20%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00681)</td>
<td>(0.00554)</td>
<td>(0.00657)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Middle-Age</strong></td>
<td>0.06670 ** **</td>
<td>0.01873 ** **</td>
<td>0.04796 ** **</td>
<td>28.08%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00828)</td>
<td>(0.00541)</td>
<td>(0.00703)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Old-Age</strong></td>
<td>0.08037 ** **</td>
<td>0.02936 ** **</td>
<td>0.05100 ** **</td>
<td>36.54%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.01029)</td>
<td>(0.00742)</td>
<td>(0.00799)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Low-Education</strong></td>
<td>0.08789 ** **</td>
<td>0.04702 ** **</td>
<td>0.04087 ** **</td>
<td>53.50%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00850)</td>
<td>(0.00646)</td>
<td>(0.00588)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>High-Education</strong></td>
<td>0.08484 ** **</td>
<td>0.04002 ** **</td>
<td>0.04481 ** **</td>
<td>47.18%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.01403)</td>
<td>(0.00942)</td>
<td>(0.00971)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Household (HH) Income</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Low-HH Income</strong></td>
<td>0.06729 ** **</td>
<td>0.04186 ** **</td>
<td>0.02544 ** **</td>
<td>62.20%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00943)</td>
<td>(0.00787)</td>
<td>(0.00637)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Med-HH Income</strong></td>
<td>0.08234 ** **</td>
<td>0.04072 ** **</td>
<td>0.04162 ** **</td>
<td>49.45%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00928)</td>
<td>(0.00689)</td>
<td>(0.00649)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>High-HH Income</strong></td>
<td>0.07169 ** **</td>
<td>0.03942 ** **</td>
<td>0.03227 ** **</td>
<td>54.99%</td>
</tr>
<tr>
<td><strong>Effect</strong></td>
<td>(0.00930)</td>
<td>(0.00698)</td>
<td>(0.00626)</td>
<td></td>
</tr>
<tr>
<td><strong>Shape</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Sampling weights are applied. Linearised standard errors in parentheses. *** denotes p < 0.01, ** denotes p < 0.05, * denotes p < 0.1. Young-Age implies 18–39 years old; Middle-Age implies 40–59 years old; Old-Age implies 60 years old and above. Low-Education implies Completed Year 12 or less and/or Certificate I/II/III/IV or other certificates; High-Education implies Completed Diploma or Advanced Diploma or Bachelor or higher. Low-HH Income implies 1st to 3rd decile; Medium-HH Income implies 4th to 7th decile; High-HH Income comprises of 8th to 10th decile.
dimension by underlining density growth at both ends of the distribution, not just at the upper end. Our results also concur with findings for other countries. For instance, Flegal and Troiano (2000) show that increasing upper-tail distributional skewness is more marked in women than men in the US. Whereas, Contoyannis and Wildman (2007) report polarisation (mostly to the lower-tail) of the (general) body mass distribution of women in Canada and England. By age groups, there are also distinct polarisation patterns. In the middle-age group, a greater portion of the mass (about 9% out of a mass shift of 15%) moved to the upper part of the general body mass distribution, while in the young-age group, most of the mass (7% out of a mass move of 11%) shifted to the lower part of the distribution. In the old-age group, on the other hand, there is an almost symmetric density movement as about 7% shifted to the lower and upper portions of the general body mass distribution.

### 5.3.2.2. By socio-economic characteristics.

Across the educational groups, the location effect accounts for 47%—67% of general and 67–68% of central body mass distributional changes. A similar pattern of results is observed in the household income groups.

<table>
<thead>
<tr>
<th>Body Mass Index (BMI)</th>
<th>MRP</th>
<th>LRP</th>
<th>URP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Sample</td>
<td>0.1236 **</td>
<td>0.11106 **</td>
<td>0.13546 **</td>
</tr>
<tr>
<td></td>
<td>(0.00942)</td>
<td>(0.01593)</td>
<td>(0.01250)</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Women</td>
<td>0.14800 **</td>
<td>0.17324 **</td>
<td>0.12275 **</td>
</tr>
<tr>
<td></td>
<td>(0.01382)</td>
<td>(0.02358)</td>
<td>(0.01696)</td>
</tr>
<tr>
<td>Men</td>
<td>0.11108 **</td>
<td>0.05712 **</td>
<td>0.16504 **</td>
</tr>
<tr>
<td></td>
<td>(0.01359)</td>
<td>(0.02258)</td>
<td>(0.01819)</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Young-Age</td>
<td>0.10573 **</td>
<td>0.13192 **</td>
<td>0.07954 **</td>
</tr>
<tr>
<td></td>
<td>(0.01594)</td>
<td>(0.02603)</td>
<td>(0.02100)</td>
</tr>
<tr>
<td>Middle-Age</td>
<td>0.14922 **</td>
<td>0.12257 **</td>
<td>0.17587 **</td>
</tr>
<tr>
<td></td>
<td>(0.01612)</td>
<td>(0.02663)</td>
<td>(0.02158)</td>
</tr>
<tr>
<td>Old-Age</td>
<td>0.14765 **</td>
<td>0.15486 **</td>
<td>0.14044 **</td>
</tr>
<tr>
<td></td>
<td>(0.01626)</td>
<td>(0.02675)</td>
<td>(0.02293)</td>
</tr>
<tr>
<td>Education</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Education</td>
<td>0.12769 **</td>
<td>0.12778 **</td>
<td>0.12760 **</td>
</tr>
<tr>
<td></td>
<td>(0.01394)</td>
<td>(0.02375)</td>
<td>(0.01893)</td>
</tr>
<tr>
<td>High Education</td>
<td>0.15311 **</td>
<td>0.14653 **</td>
<td>0.15668 **</td>
</tr>
<tr>
<td></td>
<td>(0.02159)</td>
<td>(0.03719)</td>
<td>(0.02664)</td>
</tr>
<tr>
<td>Household (HH) Income</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low-HH Income</td>
<td>0.09778 **</td>
<td>0.08885 **</td>
<td>0.10672 **</td>
</tr>
<tr>
<td></td>
<td>(0.01907)</td>
<td>(0.03320)</td>
<td>(0.02491)</td>
</tr>
<tr>
<td>Med-HH Income</td>
<td>0.13146 **</td>
<td>0.11964 **</td>
<td>0.14327 **</td>
</tr>
<tr>
<td></td>
<td>(0.01622)</td>
<td>(0.02788)</td>
<td>(0.02191)</td>
</tr>
<tr>
<td>High-HH Income</td>
<td>0.11210 **</td>
<td>0.08315 **</td>
<td>0.14105 **</td>
</tr>
<tr>
<td></td>
<td>(0.01746)</td>
<td>(0.02876)</td>
<td>(0.02388)</td>
</tr>
</tbody>
</table>

**Note:** Sampling weights are applied Linearised standard errors in parentheses. * **denotes p < 0.01, * * denotes p < 0.05, * denotes p < 0.01.

In the sub-time periods, we discern density changes that are relatively diminished at the upper deciles. Additional analyses then disclose unique patterns of distributional density movements in the socio-economic groups. For instance, in the educational groups, there is an almost symmetric mass shift from the median to the upper and lower parts of the general body mass distribution. This result extends Gearon et al.’s (2015) findings (of a more right-tailed skewed body mass distribution among low-educated than high-educated adults) to underscore (once again) that the shape change of the body mass distribution in Australia is far more encompassing—and goes beyond mere growing upper-tail skewness. Also, whereas in the medium and high-household income groups, the larger density share moved to the upper-tail of the general body mass distribution, in the low-household income group, almost all (4.9% out of a total mass shift of 5.3%) moved to the lower-tail of the central body mass distribution.

### 6. Conclusion

In this study, we implement two distinct distributional methods—inequality indices and relative distributions (RD)—to investigate changes of body mass in the Australian population between 1995 and 2017. Besides assessing the specifics of distributional density and inequality changes, our chosen methods also probe into the sources of body mass changes. Our results indicate that inequality of body mass, a measure of health and multi-dimensional wellbeing, has risen over the 22 year period of our study. Further analyses disclose that the inequality growth of (general) body mass during the early period surpasses that of the recent period. All results are robust as GE(0) and G(1) also reveal inequality increases of similar magnitudes. The stability of our results (across the different indices) underscores an important aspect about the growth of inequality of body mass in Australia: there is growth of inequality throughout the body mass distribution, not just at the upper or lower part. Furthermore, besides the distribution-wide increase in inequality, our results also reveal that inequality is larger at the upper part (associated with obesity) than the lower part of the body mass distribution.
Fig. 3. Relative PDF By Demographic Characteristics, Entire Period.
Fig. 4. Relative PDF Decomposition By Demographic Characteristics, Entire Period. Note: Sampling weights are applied.
Using demographic and socio-economic sub-population groupings, we uncover more about the growth of body mass inequality in Australia. Specifically, while there is an increase in body mass inequality across all sub-population groups, the magnitude of growth is always higher in women, young-age, low-education, and low-household income groups. Additional analyses, however, suggest that demographic and socio-economic characteristics explain little of the total inequality. The results lead to our first main conclusion, that in Australia, growing body mass inequality is a population-wide phenomenon. Such findings, however, are not restricted to Australia as Nie et al. (2019), Nie et al. (2021) and Pak et al. (2016) also reach the same conclusion for other developed (US) or developing (China and Cuba) countries.

Supplementing inequality indices, the RD method offers a non-parametric distributional perspective on body mass changes in Australia between 1995 and 2017. The first main RD-based result highlights significant growth (since 1995) in the proportion of Australian adults falling into the upper deciles of the body mass distribution, with the largest density disparity found at the uppermost 9th decile. Moreover, these density changes are not due to demographic or socio-economic compositional changes because, when controlling for compositional changes over time, the within sub-population groups analysis discloses comparable results of more density at the upper parts of the body mass distribution.

In trying to determine the source of the change, the location effect (reflecting body mass rises across the entire population) is often revealed as the more influential force. This result also holds across most of the sub-population groups. When analysing the sub-time periods, we discern that the location effect’s dominance does in fact grow over time. The results lead to our second main conclusion: body mass distributional change in Australia between 1995 and 2017 is driven by body mass increases across the entire (adult) population. Our conclusion underscores that, even though individuals’ lifestyle behaviours (food consumption habits, physical activities etc.) impact body mass, they reflect the influences of the broader physical and social environment affecting the entire population. In particular, they appear to highlight the contributions of an obesogenic environment that fosters body mass gains across the population as a whole. Based on birth-cohort analysis, the studies of Allman-Farinelli et al. (2008) and Australian Institute of Health and Welfare (2017) also lend support to the view of an increasing obesogenic environment in Australia.

Our finding that the main source driving body mass changes operates broadly across the Australian population, suggests that mitigation programs and policies need to be inclusive and must target the entire population. Thus, it may be prudent to invest in programs and policies, such as food nutrition literacy programs, food pricing measures, provision of healthier food options in schools and workplaces, etc. to reap tangible future benefits. Our solutions are consistent with other policy suggestions that seek to mitigate the risk of these behaviours becoming more entrenched in the population (see for example, Commonwealth of Australia, 2022; Obesity Policy Coalition, 2020). They also underline the need for nationally coordinated intervention measures (Sacks and Robinson, 2019). Although our solution underscores the importance of

Fig. 4. (continued).
taking a broad population-based approach, adults at the higher end of the obesity spectrum need more attention as they may still be within the high-risk range even after successful interventions. Hence, it is also imperative to design intervention strategies that target those at greater risk exclusively, so that they may move into less precarious ranges.

Meanwhile, even though the contribution of the shape effect is (often) smaller, it still plays a non-trivial role in driving body mass distributional changes in Australia, and especially for general than central body mass. Using our novel analytical tool of RD, we are able to build on the findings of Peeters et al. (2015) and Walls et al. (2010) about the specifics of the shape change to the body mass distribution in Australia. Thus, we reveal that the body mass distributional shape change in Australia is far more nuanced than mere growing upper-tail skewness. Specifically, it is characterised by a growth in the proportion of adults at both ends of the body mass distribution, while the proportion at the centre hollows out (polarisation). Moreover, our results also reveal that, the shape effect (again, in the form of polarisation) is largely responsible for the change in the general body mass distribution of women. In terms of the specifics of the density change, and in light of past studies, our results were unexpected. They highlight that, among women of normal weight who have moved to the distributional tails between 1995 and 2017, the (slightly) larger share shifted to the underweight range than to the obese range. Thus, while in general, it is important to take a broad population-based approach to address the trend of growing obesity in Australia, our findings also emphasise that, in women, to make impactful changes, we have to focus on reversing the shape changes to the body mass distribution. As such, there is a need to investigate the factors that are driving density changes from the middle to, not just the upper (obese) but also the lower (underweight) part of the distribution. Since underweight is also clinically risky category (Katzmarzyk et al., 2001; Lorenz et al., 2017; Roh et al., 2014), we have to determine whether factors, such as perceptions of ideal body shape (Brown and Slaughter, 2011), media influences (Grabe et al., 2008; Romo et al., 2016), etc. are at work, leading women of normal weight to become underweight over time in Australia.

Finally, we garner distinct results for general (BMI) and central (WHtR) body mass in most of our analyses. As such, anti-obesity campaigns need to be precise about whether they intend to target unhealthy general and/or central body mass. Specifically, given that general and central body mass cannot be treated interchangeable as they have different inequality and source (as well as health risk) profiles, therefore, it is prudent to consider whether the attention of mitigation measures should be on general or central body mass. It may be that central body mass should take priority because there is ample evidence indicating that it is a better predictor of health risks. This then suggests that intervention strategies should focus on reversing the overall rightward shifting of the (central) body mass distribution to tackle the growing incidence of unhealthy body mass in Australia.

Acknowledgements

This study uses the Basic CURF data from the Australian Bureau of Statistics (ABS). The findings and the conclusions reached using the data are those of the authors, and should not be attributed to ABS.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehb.2023.101270.

References


Dow, J., 2008. Using relative distributions to investigate the body mass index in England and Canada. Health Econ. 16 (9), 944.


