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Defining and Measuring Health Poverty

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Defining and Measuring Health Poverty

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Abstract

The aim of the paper is twofold: first we elaborate how the concept of 'health poverty' can be defined and measured, and second we apply the methodology to study health poverty in a variety of cases. Although not entirely new, the notion of health poverty is seldom used – in contrast to the notion of income poverty. In our view a particular poverty concept focusing on health is useful and relevant, especially for public health policy. The measurement of health poverty allows us to gain insights into different sorts of health deprivation in society as a whole, and in specific subgroups.

Perhaps the main reason why there exist relatively few studies on health poverty is that in comparison to income, health is multifaceted and therefore much harder to measure accurately. The first choice to be made is that of the health variable which will be taken into consideration. We will look at three different variables, all of which are assumed to have ratio-scale properties. This means that we can calculate the distance of everyone's health achievement from a given threshold level and compare the differences between individuals. We are then in a position to measure health poverty by means of the now widely adopted Foster-Greer-Thorbecke (FGT) class of poverty indicators. In our application we look at poverty with respect to cardiovascular risk, general health status, and life expectancy. As far as we can see, this approach has never been followed before.

The FGT class of poverty measures includes a poverty aversion parameter. Different values of the parameter will be assumed in order to assess three aspects of poverty (incidence, intensity and inequality, known as the three I's of poverty measurement). Moreover, the FGT class is additively decomposable, which makes it possible to gauge the contribution of poverty within specific subgroups to overall poverty.

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1. Introduction

The aim of the paper is twofold: first we elaborate how the concept of 'health poverty' can be defined and measured, and second we apply the methodology to study health poverty in a variety of cases. Although not entirely new, the notion of health poverty is seldom used – in contrast to the notion of income poverty. For instance, in a recent survey on poverty and inequality it is mentioned only once (Rohwerder, 2016: 3). It does have its place in the literature on multidimensional poverty (e.g., Ravallion, 2011; Weziak-Bialowolska, 2016). In our view a particular poverty concept focusing on health is useful and relevant, especially for public health policy. There is, of course, a large body of work on the health disadvantages faced by specific groups, such as indigenous people, in comparison to the rest of society. For example, in Australia the 10-year lower life expectancy of Indigenous Australian's has been a key measure of what have been termed health gaps (Close the Gap Campaign Steering Committee, 2017). The measurement of health poverty allows us to obtain insights into different sorts of health deprivation in society as a whole, and in specific subgroups.

Perhaps the main reason why there are relatively few studies on health poverty is that in comparison to income, health is multifaceted and therefore much harder to measure accurately. The first choice to be made is that of the health variable which will be taken into consideration. The nature of the health variable affects the way health poverty should be measured, as it does in the case of (socioeconomic) inequality of health (Erreygers and Van Ourti, 2011). Sometimes health is measured by means of a categorical or qualitative variable. A good example is provided by self-assessed health: in many household surveys people are asked to assess their health status by selecting one state from a fixed list of possible health states. This sort of qualitative information entails the use of ordinal poverty measures (Allison and Foster, 2004; Madden, 2015), such as the class of ordinal poverty indicators proposed by Bennett and Hatzimasoura (2011). These measures have already been applied by Brzezinski (2015) to estimate the trends in health poverty in Britain over the period 1991-2008, and by Pascual, Cantarero and Lanza (2017) to do the same for Spain in the period 2008-2016. Alternatively, Simões et al. (2016) constructed a quasi-objective health variable based on the EQ-5D index scores of individuals. Their variable lies between 0 and 1 and allows a more refined analysis of health poverty. In fact, they do much more than that: they estimate not only health poverty, but also health 'richness', based on uniform cut-off points determining whether individuals are health poor or health rich.

Our approach is based on the assumption that the health variable has ratio-scale properties. In comparison to the case of an ordinal health variable, the advantage is that we can attach meaning to the distance of everyone's health achievement from a given threshold level, which we call the 'health gap' for those who do not reach the threshold. In addition, we allow for the possibility that the relevant threshold levels may differ from one individual to the other, e.g. according to whether a person is young or old. We then measure health poverty by means of the now widely adopted Foster-Greer-Thorbecke (FGT) class of poverty indicators (Foster, Greer and Thorbecke, 1984).

We begin by a more detailed explanation of our health poverty measurement procedure (section 2). Since the class of FGT poverty measures includes a poverty aversion parameter, we will assume different values of the parameter in order to assess three aspects of poverty (incidence, intensity and inequality, known as the three I's of poverty measurement). We then show that our health poverty measures are additively decomposable, which makes it possible to gauge the contribution of poverty within specific subgroups to overall poverty (section 3). After that, we explore how we can estimate to what extent health poverty is related to income, i.e. whether health poverty has a socio-economic gradient (section 4). We apply our methodology to three different situations, involving the risk of contracting cardiovascular diseases (CVD), preference based measures of health status, and life expectancy. To assess CVD-related health poverty we will use American data (section 5). For the two other types of health poverty we will use Australian data (section 6). We end with a few concluding remarks and proposed agenda for future research (section 7).

2. The measurement of health poverty

In this section we explain the mechanics of health poverty measurement, assuming that health is a variable with ratio-scale properties. The guiding idea is to consider as health poverty the condition of being in 'poor health', i.e. of having a health status worse than what is considered to be minimally acceptable. There are basically two ways of defining health poverty standards: either we adopt a uniform threshold ('one size fits all'), or we allow for variation, say different thresholds for men and women. The second approach relies on the assumption that what constitutes the level of minimally acceptable health may depend on the average health achievement of an individual's specific reference group.

Our health poverty measures are based on the normalized health poverty gaps of individuals. The health poverty gap is basically the distance of an individual's health attainment h_i from this individual's health poverty threshold; it is 'normalized' if it is expressed as a fraction of the threshold. In the case of a uniform health poverty standard z, the normalized health gap g_i is defined as:

$$g_i \equiv \begin{cases} \dfrac{z - h_i}{z} & \text{if} \quad h_i < z \\ 0 & \text{if} \quad h_i \geq z \end{cases} \tag{1}$$

In the case of differentiated health poverty standards, the gap must be defined with respect to an individual's specific health poverty standard. More formally, suppose there are *n* individuals in society, designated by the set $N = \{1, 2, \ldots, n\}$, and let $J \subseteq N$ be a given reference group consisting of n_J individuals. Assume every individual belongs to one and only one reference group, and let the health poverty threshold for reference group J be z_J. Then for any individual $i \in J$ we can define the normalized health gap as:

$$g_i \equiv \begin{cases} \dfrac{z_J - h_i}{z_J} & \text{if} \quad h_i < z_J \\ 0 & \text{if} \quad h_i \geq z_J \end{cases} \tag{2}$$

How many reference groups there should be, is open to debate. For instance, in health inequality measurement it is usual to standardize for characteristics such as sex and age. The degree to which we should standardize for other characteristics depends on whether these are seen as legitimate or fair grounds for distinction (see Fleurbaey and Schokkaert, 2009, for further discussion). Similarly, there is more than one way to define the uniform or group-specific health poverty thresholds.

Once the threshold values have been determined, we can say that all those whose health achievement falls below the relevant threshold value are health poor, and that the extent of their health poverty is captured by their health gaps. Our aggregate health poverty measures are defined as functions of the normalized health gaps g_i. More specifically, the FGT index measures health poverty as follows:

$$P_\alpha = \frac{1}{n} \sum_{i=1}^{n} (g_i)^\alpha \tag{3}$$

where α is a non-negative poverty aversion parameter. We will consider different values of this parameter, viz. $\alpha = 0,1,2$. It is well-known that P_0 is the headcount ratio, P_1 the poverty gap ratio and P_2 the squared gap measure (Foster, Greer and Thorbecke, 2010).

As can be seen from (1) and (2), if the threshold values are lowered but the health achievements remain the same (e.g., as a result of a change in the threshold definition), the normalized gaps either decrease (if they were positive) or remain equal to zero. It follows from (3) that this leads to a reduction or to a status quo of the measured degree of poverty.

We apply this framework to different health variables. Our first application concerns risk, or rather its complement, which we designate by the term 'resilience'. The absolute risk of the occurrence of disease over a defined period (e.g., 10 years) is now increasingly used as a clinical tool. For example, most guidelines for the use of treatments for cardiovascular disease (CVD) employ risk assessment (D'Agostino et al., 2013). Along these lines we assume the CVD risk of individual *i* to be equal to r_i, a scalar which varies between 0 and 1. The CVD resilience of individual *i* is defined as $1 - r_i$. We take CVD resilience as our health variable ($h_i = 1 - r_i$). For this health variable we assume there are no grounds to treat individuals differently, and therefore we adopt a uniform threshold level z. If we define the critical CVD risk level as equal to 20%, which historically was a level where treatment is initiated (Lloyd-Jones, 2010), then the corresponding CVD resilience poverty threshold is equal to $z = 80\%$. Such a threshold is clinically meaningful as the prescribing of therapies to prevent cardiovascular disease is now based on absolute risk thresholds (Jackson et al., 2005). Since we have a uniform threshold, the normalized CVD resilience gaps of individuals are defined according to formula (1).

We can then proceed to calculate the CVD poverty rate by means of the FGT index. Once we know the CVD poverty rate, we will compare the existing situation to two hypothetical ones. In the existing situation, some people with high CVD risk levels are treated with drugs, and as a result have reduced risk levels. Suppose now that no-one received these drugs; this would increase the risk levels of those who are now treated with drugs. We can call this the all-excluded scenario. Alternatively, suppose that everyone who has a risk level above the critical value were treated with risk-reducing drugs; this would decrease the risk levels of previously untreated high-risk individuals. This is the all-included scenario. We will calculate the effect of both policies on the CVD poverty levels.

Our second application involves measures of health status which are now routinely included in population health surveys. A good example is the Short Form (36) Health Survey, a 36-item survey of health status which has been included in population health surveys (Maglinte, 2012). While responses to the SF-36 are summarised through a series of domains, health economists often prefer the use of measures such as SF-6D which have preference-based weighting of items responses to enable to form the basis of the quality component of quality-adjusted life years (Brazier, 2002).

Here we denote the univariate health status variable SF-6D, which is sometimes referred to as a 'utility' index, by q_i. In this case, our health variable ($h_i = q_i$) ranges between 0 (a state of very poor health equivalent to death) and 1(full health). In contrast to the first application, we now assume that the threshold values are not uniform. The reference groups are defined in terms of age and sex. We opt to derive our threshold value z_J for reference group J from the average health achievement $\bar{q}_J = \frac{1}{n_J}\sum_{j \in J} q_j$ of this group. More specifically, we adopt a relative approach: we assume the poverty threshold is a fraction λ below the average health achievement of the reference group. Hence, the poverty threshold for reference group J is $z_J = (1-\lambda)\bar{q}_J$. An alternative approach, which we do not explore here, would be to define the poverty threshold in absolute terms, which would give $z_J = \bar{q}_J - x$.

Our final application focuses on life expectancy. Peltzman (2009) has proposed examining inequalities in the distribution of mortality across age using what he terms 'Mortality Ginis'. Using his approach, a hypothetical egalitarian distribution would involve all people dying at the same age. The analogous poverty measure to Mortality Ginis would be defined using age-based thresholds (e.g., living to the age of 20) and the poverty measure would be related to the proportion of all deaths that occur before this age. While such measures could be applied to existing aggregate data, such as country level lifetables, it is also important to recognise that there is significant individual variation within age groups in mortality. Many empirical studies have shown that rates of mortality are associated with a range of behaviours such as smoking, socioeconomic factors (e.g., income) and even cohabitation status (e.g. Gerdtham, and Johannesson (2000), Clarke and Leigh (2011)).

Here we explore a poverty measure based on lifetime estimates of mortality which we summarize as an individual's life expectancy e_i, and assume that this can be estimated based

on a wide range of factors that are measured in population surveys (Karlsson et al., 2008). The expected age at death is the sum of the age and the predicted remaining life years of a person. If a_i is the age of person *i*, then $d_i \equiv a_i + e_i$ is this person's expected age at death. Let $\bar{e}_J$ be the average life expectancy of the members of reference group *J*, i.e. $\bar{e}_J = \left(\sum_{j \in J} e_j\right) / n_J$. Assuming that all members of group J have the same age a_J, the average expected age at death of any person belonging to this group is equal to $\bar{d}_J = a_J + \bar{e}_J$.[1] If for person $i \in J$ the expected age at death lies above this average expected age at death, i.e. if we have $d_i > \bar{d}_J$ or equivalently $e_i > \bar{e}_J$, then this person is relatively well-off in health terms. Health poverty concerns those who have a predicted age at death significantly below that of their reference group. In this application, therefore, the health variable we are focusing on is expected age at death ($h_i = d_i$), and as reference values for the determination of the poverty thresholds we take the group-specific average expected age at death ($\bar{d}_J$).

As in the previous case, we follow a relative approach to define poverty thresholds. The thresholds are defined by deducting a fixed fraction λ from the group-specific average expected ages of death. The threshold levels are then equal to $z_J = (1-\lambda)\bar{d}_J$. For instance, λ could be fixed at 5%. We assume that any member of group J whose predicted age at death is lower than the threshold value z_J is health poor.

3. Health poverty decomposition

One of the advantages of using the FGT index to measure health poverty is its flexibility with regard to decomposition. Thanks to its simple additive structure, the health poverty index (3) is subgroup decomposable. Let the population be partitioned into *K* subgroups with sizes $n_1, n_2, ..., n_K$; these groups may, but need not, coincide with the reference groups. The population shares of these groups are denoted by $s_1, s_2, ..., s_K$, with $s_J \equiv n_J / n$. By analogy with (3), we define the poverty level in subgroup *J* by:

$$P_{\alpha,J} = \frac{1}{n_J} \sum_{j \in J} (g_j)^{\alpha} \qquad (4)$$

[1] Note that if not all individuals of reference group *J* have the same age, then the formulas that follow have to be modified slightly.

It is straightforward to see that the level of health poverty in society can be expressed as a weighted average of the levels of health poverty in the *K* subgroups, with the weights equal to the population shares:

$$P_\alpha = \sum_{J=1}^{K} s_J P_{\alpha,J} \tag{5}$$

From (5) we can derive that the contribution of subgroup *J* to the overall level of health poverty P_α, denoted by $c_{\alpha,J}$, is equal to:

$$c_{\alpha,J} = s_J \frac{P_{a,J}}{P_\alpha} \tag{6}$$

It follows that if the level of poverty in subgroup *J* is the same as the level of poverty in society as a whole, then the contribution of subgroup *J* is simply equal to its population share. Groups with higher (c.q. lower) than average health poverty contribute more (c.q. less) to health poverty than their population share.

We will use these decomposition formulas to illustrate the difference in contributions to health between different sub-groups including men and women and between smokers and non-smokers.

4. Health poverty and income

From a policy perspective, it may be important to know whether health poverty occurs more among the (income) poor than among the (income) rich. Subgroup decompositions based on income criteria will provide useful information on the relationship between health poverty and income. For instance, one could look at the levels of health poverty in different income deciles, as pointed out above. One way to link health poverty to the more traditional analysis of socioeconomic inequalities consists of measuring to what extent health poverty is correlated with income. Bivariate indicators of inequality, such as the Concentration index, allow us to estimate this type of correlation. The health poverty dimension is taken into account by treating the normalized health gaps, or more precisely the normalized health gaps raised to the power of α, as individual measures of health poverty. As far as income is concerned, we can look both at income ranks and at income levels. While the first choice characterizes rank-dependent indicators, of which the Concentration index is the most prominent example, the second choice leads to level-dependent indicators (Erreygers and

Kessels, 2017; Erreygers et al., 2018). Since the normalized health gaps are bounded variables, we will consider the bounded versions of these income-related indicators of inequality:

$$R^b(r, g^\alpha) = \frac{4}{n}\sum_{i=1}^{n}\left(\frac{2r_i - n - 1}{n}\right)g_i^\alpha \tag{7}$$

$$L^b(y, g^\alpha) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \bar{y}}{\bar{y}}\right)g_i^\alpha \tag{8}$$

where r_i stands for the income rank and y_i for the income level of person *i*, and $\bar{y}$ for the average income level in society. If health poverty occurs more frequently among those with low incomes than among those with high incomes, the values of $R^b(r, g^\alpha)$ and $L^b(y, g^\alpha)$ are negative. Larger absolute values of the indicators reflect higher levels of inequality.

It should be observed that the two income-related inequality indicators introduced above are similar, but not identical, to the more usual income-related inequality indicators measuring the association between the health variable *h* and the income ranks *r* or the income levels *y*, i.e. $R^b(r,h)$ or $L^b(y,h)$. The normalized health poverty gaps g^α are, in fact, truncated variables: for all individuals who are not health poor, the value of the health poverty gap is equal to zero. Moreover, while for health variables higher values typically denote better health status, in the case of health gaps larger values indicate worse outcomes. Hence, while a negative $R^b(r,h)$ or $L^b(y,h)$ signals that the distribution of health is biased in favour of the poor, a negative $R^b(r, g^\alpha)$ or $L^b(y, g^\alpha)$ indicates that health poverty occurs less frequently among the income rich.

Estimates of uncertainty such as confidence intervals can be obtained through bootstrapping methods. In the examples which follow we report 95% Confidence Intervals based on the percentile method using a 1000 replications of the data.[2]

[2] We have only captured the uncertainty surrounding the poverty measure and not the underlying health measure as this is not routinely reported for many measures such as Framingham Risk Scores (Ladapo and Goldfeld, 2014).

5. CVD-related health poverty

The modern approach to the prevention of cardiovascular disease involves assessing a patient's absolute risk of a cardiovascular event occurring over a defined period (e.g., 10 years). For example, the 2013 American Heart Association guidelines for the use of the cholesterol medications statins recommend an algorithm to determine whether a patient needs to be treated with Statins, a cholesterol lowering treatment. Traditionally this determination has been based on the level of cholesterol (Stone et al., 2014), but the 2013 guidelines moved to an algorithm that involved the assessment of absolute cardiovascular risk.

Cardiovascular disease risk assessment involves the use of risk equations that provide a probability that a patient will have a CVD event (e.g., a heart attack or stroke) over a defined period. The most widely used way of calculating risk is commonly known as the *Framingham Coronary Heart Disease Risk Score* which is based on data from a long-term cohort of people living in the town of Framingham, MA (USA). The Framingham study involved the collection of clinical measures and cardiovascular outcomes since the late 1950s (Syed et al., 2014). As part of this study risk prediction equations have been published that calculate the probability of a CVD event over a 10-year period based on patients' age, sex and commonly collected clinical data including systolic blood pressure, the ratio of HDL to total cholesterol, diabetes, smoking and blood pressure treatment status (D'Agostino et al., 2008).

The guidelines for the use of preventative therapies such as statins are based on thresholds that have progressively become lower over time. For example, in England, originally guidelines for the prevention of CVD recommended treatment only for those that were assessed to be at a 30% or greater risk of developing coronary heart disease over a 10-year period. Subsequently the cardiovascular risk threshold was lowered to 20% which expanded the proportion of those who were considered 'high risk' and therefore eligible for drug treatments. (World Health Organization, 2007) In 2014 the risk threshold was further decreased to 10%. A recent analysis of the implications of this new lower threshold for statin prescribing indicates that 37% of adults in England aged 30-84 years, including almost all males older than 60 and females older than 75 years, require statin therapy (Ueda et al., 2017).

There is evidence from numerous clinical trials that statins are effective in reducing the risk of CVD. A meta-analysis of 22 trials of statin versus control shows on average a 21 %

reduction in the risk of major vascular events for each 1·0 mmol/L reduction in LDL cholesterol (Cholesterol Treatment Trialists' (CTT) Collaboration, 2012). In the following illustrative example, we assume statins have this treatment effect and moreover that they have the same relative effect on all individuals regardless of their absolute risk of CVD.

To explore how poverty measures can be used to evaluate policies regarding treatment with statins we use data from two waves of the United States National Health and Nutrition Examination Survey (NHANES): 2005-2006 and 2013-2014. The NHANES study is a continuous, annual survey of the noninstitutionalized civilian resident population of the United States by the Centers for Disease Control and Prevention (CDC).[3] The data contain results of clinical examinations (including the taking of blood samples) as well as reported information on medication use and other characteristics, such as age, sex and income. A de-identified sample of the data collected can be downloaded from the internet. Between 2005 and 2013 the patents on most types of statins expired, including simvastatin in 2006 and atorvastatin in late 2012. This resulted in dramatic reductions in the out-of-pocket expenditures for these medications (Luo et al., 2016).

Table A1 in the Appendix presents descriptive information for the two waves of the NHANES survey considered in this paper. We have restricted the age range to between 30-75 years (which is the range used in many clinical guidelines for cholesterol lowering). Between the two surveys the proportion of the sample population using cholesterol lowering medications has increased by 4% ($P < 0.0001$), and that using blood pressure medications by 3% ($P = 0.0049$), reflecting the increased use of medications to prevent cardiovascular disease in the United States.

In what follows we have calculated the absolute 10-year risk of a CVD event based on the 2008 Framingham equation estimated by means of the risk factors as measured in the NHANES survey. We denote this data series as the actual risk associated with *current statin use*. The NHANES survey also collects information on whether each respondent is taking cholesterol medications. We use this information to calculate estimated CVD under two additional scenarios. The first scenario, which we call *no use of statin medications*, involves adjusting upward the risk of those individuals currently taking statin medications by a factor of 1.26. This is equal to the ratio of 1 to 0.79, where 0.79 reflects the 21% risk reduction conferred by statins. The adjusted risk is an estimate of the risk individuals currently taking

[3] More information can be found here: https://wwwn.cdc.gov/nchs/nhanes/.

statin medications would face if they were not taking any cholesterol medications. The second scenario is *universal use of statin medications* and involves adjusting downward the risk of all individuals currently not taking statins by a factor of 0.79. This is again based on the assumption that the use of statins reduces risk by 21%.

As explained previously, our health poverty threshold is based on a 10-year CVD risk level of 20%. We measure the proportion of the population that would be recommended for treatment with statins under various treatment policies. Figure 1 illustrates the absolute risk in 2005-2006 under the three scenarios outlined above. We rank the population from lowest to highest risk, similar to Pen's 'Parade of Dwarfs' often used to represent income inequality (Pen, 1971: 48-59). Under the *no use of statin medications* scenario (represented by the blue line) 79.3% of the population would be below (and 20.7% above) the critical CVD risk threshold. The actual use of statins in 2005-2006 (represented by the green line) resulted in a rightward shift in the line representing the distribution of risk. This increases the proportion below the threshold (i.e. 81.1% of the population has a 10-year CVD risk below 20%). Hence statins have resulted in around 1.8% of the US population moving below the 20% risk threshold. The final scenario, *universal use of statin medications* (represented by the red line), illustrates the hypothetical maximum gain from universal treatment. This would further increase the proportion of the population below the threshold (i.e. around 85.1% of people would have a risk below 20%, or an additional 4% of the population). What this scenario quantifies is the excess risk above 20% that could potentially be removed by statin treatments.

Figure 1: Cardiovascular risk of the US population (aged 30-75 years) in 2005-2006

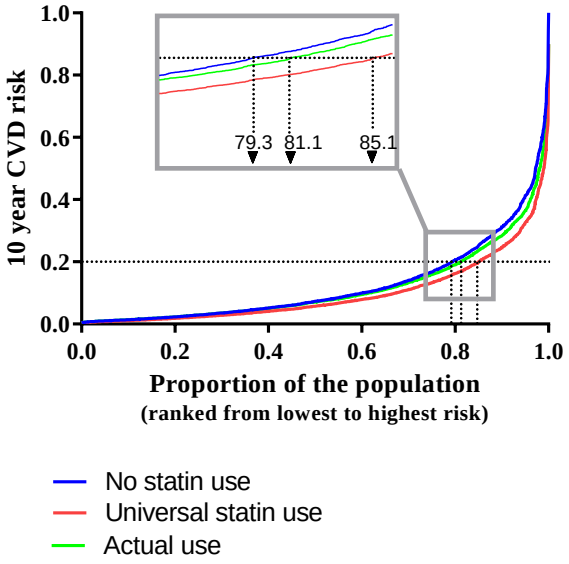
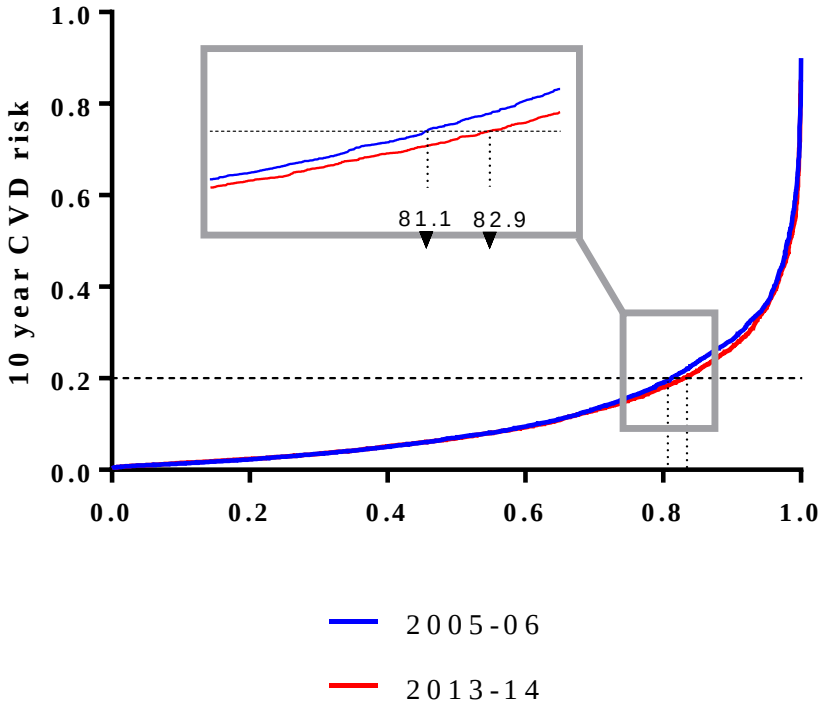


Figure 2 compares the CVD risk associated with the actual use of statins at two points in time, 2005-2006 and 2013-2014. As previously discussed, there has been a dramatic decline in the cost of most commonly used statin medications over this period and a significant rise in the overall use. How has this impacted on the distribution of CVD risk around a 20% threshold? Figure 2 illustrates the outward shift of the CVD risk curve between 2005-2006 and 2013-2014. As a result of the changes, an additional 1.8% of the sample population have seen their risk reduced to a level below the critical CVD risk threshold: the proportion below the 20% CVD risk threshold has increased from 81.1% to 82.9% over the period.

Figure 2: Comparison of actual cardiovascular risk over time



The use of clinical thresholds to determine whether a patient should receive treatment has strong parallels with the measurement of poverty. The intent of clinical guidelines for the treatment of CVD is to target treatment at patients deemed at a high risk. Measures tracking the proportion of the population above a threshold (e.g. 20% 10 year risk) provide information on the overall performance in the prevention of CVD. As explained in section 2, we measure CVD-related health poverty by looking at the CVD resilience gaps of individuals. The proportion of the population that exceeds a certain CVD risk (e.g. those deemed at high risk) is captured by the headcount ratio, i.e. the poverty measure P_0. The poverty gap ratio P_1 and the squared gap measure P_2 both provide measures of the degree to which CVD risk exceeds a given threshold.

Table 1: Different measures of CVD-related health poverty

	Headcount ratio P_0 (z = 0.8)			Poverty gap ratio P_1 (z = 0.8)			Squared gap measure P_2 (z = 0.8)		
	2005-2006	2013-2014	Difference	2005-2006	2013-2014	Difference	2005-2006	2013-2014	Difference
No treatment (NT)	20.71% 19.31% 22.15%	19.30% 18.07% 20.57%	−1.42% −3.43% 0.56%	3.80% 3.46% 4.21%	3.53% 3.22% 3.87%	−0.27% −0.79% 0.25%	1.31% 1.13% 1.56%	1.23% 1.05% 1.43%	−0.08% −0.36% 0.19%
Current treatment (CT)	18.86% 17.45% 20.23%	17.08% 15.96% 18.28%	−1.78% −3.69% 0.03%	3.03% 2.74% 3.39%	2.65% 2.40% 2.91%	−0.38% −0.78% 0.04%	0.90% 0.77% 1.07%	0.77% 0.66% 0.89%	−0.12% −0.32% 0.06%
Universal treatment (UT)	14.92% 13.72% 16.22%	13.90% 12.80% 15.07%	−1.02% −2.69% 0.66%	2.08% 1.86% 2.36%	1.92% 1.71% 2.15%	−0.16% −0.50% 0.19%	0.55% 0.46% 0.68%	0.52% 0.44% 2.15%	−0.03% −0.18% 0.11%
Difference (NT)-(CT)	1.85% 1.37% 2.37%	2.22% 1.77% 2.69%		0.77% 0.68% 0.87%	0.88% 0.79% 0.98%		0.41% 0.33% 0.50%	0.45% 0.38% 0.54%	
Difference (UT)-(CT)	−3.94% −4.63% −3.26%	−3.18% −3.73% −2.58%		−0.95% −1.05% −0.85%	−0.73% −0.82% −0.66%		−0.35% −0.41% −0.28%	−0.25% −0.30% −0.21%	

Note: The 95% confidence intervals are indicated in small print below the estimates. These were obtained via bootstrapping (1000 replications).

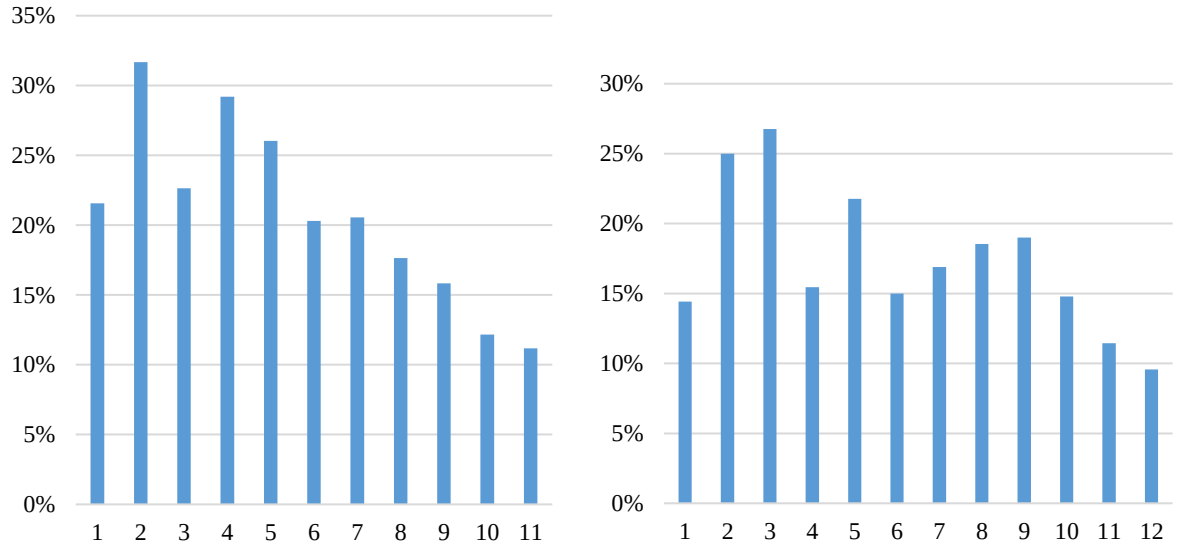
Source: own calculations, based on data from the NHANES surveys of 2005-06 and 2013-14.

Table 1 reports the three measures of poverty. While the headcount ratio poverty measures accord with those reported in Figures 1 and 2, the other measures can be explained intuitively: the poverty gap is the degree to which average risk exceeds the threshold for those deemed at high risk (i.e. > 20%), while the squared gap measure places even greater weight on those at the highest risk. In terms of the headcount ratio, moving from the current treatment to universal treatment would have a higher absolute effect of the level of health poverty (−3.94% and −3.18%) than moving to no treatment at all (1.85% and 2.22%), but in terms of the other poverty measures the picture is less clear. In this regard, poverty measures are useful in quantifying the medical concept of a 'treatment gap' which is often defined as the number of people with a condition or disease who need treatment for it but who do not get it (Kale, 2002). Here, the treatment gap would equate to the difference between current and universal treatment described above.

Finally, we look at the relationship between CVD-related health poverty and income conditions. For most individuals, the NHANES database contains information on their household income category.[4] In the 2005-06 survey the variable INDFMINC assigns individuals to one of 11 income groups according to their annual family income, with group 1 having an annual family income between 0 and 4,999 USD, and group 11 an annual income of 75,000 USD or higher. In the 2013-14 survey, however, the variable IND235 assigns individuals to 12 income groups according to their monthly family income, with group 1 having a monthly income between 0 and 399 USD, and group 12 a monthly income of 8,400 USD or higher. Figure 3 represents the P_0 poverty rates in each of these income groups for both surveys. With the exception of income groups 1, 3 and 6, a clear social gradient is present in 2005-06, with CVD-related health poverty rates getting smaller as income increases. The pattern is less clear in 2013-14; it seems that the association between income and CVD-related health poverty has become weaker. This is confirmed by the values of the (bounded) Concentration index $R^b(r,h)$, calculated assuming that all individuals within a given income group have the same income rank. For 2005-06 the index is equal to −0.0334, indicating that, as expected, income and CVD-related health poverty are negatively associated. For 2013-14 the value of the index drops to −0.0242, which is still negative but smaller than before.

[4] There are missing or insufficient data for 110 individuals of our 2005-06 sample, and for 414 individuals of our 2013-14 sample, which amounts to a loss of respectively 3.77% and 10.80% of our observations.

Figure 3: CVD-related health poverty headcount ratios in different income groups for 2005-06 (panel A) and 2013-14 (panel B)



Panel A Panel B

Source: Own calculations, based on NHANES data from surveys 2005-06 and 2013-14.

6. Health poverty in Australia

We now illustrate how we can gain insight into health poverty in Australia based on estimates of people's quality of life and estimates of life expectancy. We also decompose health poverty according to different group classifications, based on gender, smoking habits and ethnicity, and we estimate to what extent health poverty is related to income. For the empirical estimates we use data from the *Household, Income and Labour Dynamics in Australia* (HILDA) Survey which is a household-based panel study which collects a wide range information about economic and personal well-being, labour market dynamics, family life and health status (including use of the Short-Form (SF-36) health status instrument) (http://melbourneinstitute.unimelb.edu.au/hilda). The HILDA survey has involved annual interviews between 2001-2015.

Our measure of health status consists of SF-6D scores derived from questions in the SF-36 health survey that is a widely used measure of health-related quality of life. The SF-6D is

composed of six multi-level dimensions: physical functioning, role limitations, social functioning, pain, mental health and vitality that are measured on an index anchored at 1 for full health and 0 for dead (Brazier et al., 2002). We use the values for the SF-36 health survey that are reported as part of the publicly released HILDA data set.

Our estimates of life-expectancy are derived empirically by taking advantage of the matching of HILDA survey respondents to Australia National Death Index (Summerfield, 2016) so that a year of death is recorded in the public data set. To simplify the estimation of life expectancy we use a proportional hazards survival regression model using a Gompertz parametric form, which has been shown to perform well in modelling human survival and in modelling life expectancy of the HILDA participants (Clarke and Leigh, 2010).

We adopt a life-table approach so that individual age is used as the time at risk. This implies that the mortality experience of HILDA respondents at different ages provides estimates of the hazard and survivor functions for individuals over their remaining lifetime. Individual life expectancy was conditioned on a wide range of explanatory variables as reported in the first wave of HILDA including age, sex, born in Australia or elsewhere, indigenous or not, socioeconomic conditions (marital status, education level, income, labour force status, father's unemployment record), lifestyle choices (smoking), and health (general health status, bodily pain, social functioning). The definitions of the variables and summary statistics are in Table A2 of the Appendix. The continuous variables (income and health status measures) were transformed to variables that measure the deviations from the mean value in each age/sex category. Our estimation procedure ensures that for every age and sex group the average predicted life expectancy approximates the observed life expectancy reported for the Australian population (see Table A3 of the Appendix).

Table 2 provides details on the coefficients of the Gompertz proportional hazard survival regressions models for men and women, as several variables (e.g. income) have a differential effect by gender. The estimated coefficients $\boldsymbol{\beta}$ and γ form the basis of an empirically derived survivor function for each individual i:

$$S(a_i) = \exp(-\exp(x_i\boldsymbol{\beta})\gamma^{-1}(e^{\gamma a_i} - 1)) \tag{9}$$

where a_i is the years of age and x_i a vector of explanatory variables. Life expectancy e_i is then calculated by using standard life table methods (Lee and Wang, 2003). The same estimated equation is applied to all survey waves to provide estimates of life expectancy for

individuals that are dependent on covariates which can change over time (e.g., changes in health status as measured by domains of the SF-36). Finally, the average age at death was estimated by adding the life expectancy to the age at the time of the survey. On this basis the average age at death of the HILDA cohort over all the waves was estimated to be 81.1 years for men and 86.6 for women.

To identify health poverty we use a threshold equal to 95% of each group's reference level $(\lambda = 0.05)$ for both measures of health status and life expectancy. At the mean age this equates to an SF-6D health status score that is on average 0.04 units lower and for life expectancy around 4 years shorter than the average life expectancy for the reference group.

Table 2: Regression coefficients of the life expectancy estimation

	Men (*n* = 11,943)			Women (*n* = 12,877)		
	Coefficients	Z score	Hazard ratio	Coefficients	Z score	Hazard ratio
12 years or more of education	0.077	0.96	1.081	–0.014	–0.11	0.986
Current smoker		4.92	1.629	**0.483**	3.65	1.621
Currently married	**–0.446**	–5.40	0.640	–0.112	–1.22	0.894
Rural region	**–0.208**	–1.98	0.812	–0.205	–1.5	0.814
Real equivalent household income	**–0.007**	–3.38	0.993	0.000	0.21	1.000
Bodily pain	0.038	1.81	1.038	0.044	1.89	1.045
General health	**–0.147**	–6.11	0.864	**–0.099**	–3.44	0.906
Mental Health	**0.078**	2.67	1.081	**0.067**	1.99	1.070
Physical functioning	**–0.066**	–3.22	0.936	**–0.105**	–4.56	0.900
Health transitions	–0.057	–1.61	0.944	0.021	0.4	1.022
Role-emotional	–0.002	–0.18	0.998	0.006	0.42	1.006
Role-physical	–0.007	–0.49	0.993	0.006	0.36	1.006
Social functioning	–0.025	–1.08	0.975	**–0.063**	–2.44	0.939
Constant	**–11.500**	–46.58		**–12.36**	–40.34	
Gamma	**0.110**	36.04		**0.111**	30.58	

Notes: Coefficients in bold significant at $P < 0.05$.

We report the results for the FGT poverty indices P_0, P_1 and P_2 for SF-6D and life expectancy in Table 3 and in Figures A1 and A2 of the Appendix. As far as SF-6D is concerned, the headcount ratio for the population as a whole tended to fluctuate around a value of 33%. Two phases can be distinguished. Between 2001 and 2009 health poverty decreased significantly, with the headcount ratio falling from 35.36% to 31.09% ($\Delta = -4.27\%$). However, between 2009 and 2015 the decrease has come to a halt and health poverty rates have increased to their original levels ($\Delta = 4.55\%$). The poverty gap ratio and the squared gap measure indicate similar trends. It seems that 2009 was a turning point, possibly related to the global economic recession. Health poverty in terms of life expectancy is lower, with the headcount ratio averaging around 22%. The three poverty rates also show a decreasing trend up until 2009. Since then there is some evidence of a rise in poverty rates, but to a lesser extent than for SF-6D poverty.

Interesting results can be obtained by various decompositions of poverty for both quality of life and life expectancy.[5] In Table 4 we report the life expectancy poverty headcount ratios for men and women, smokers and non-smokers, and indigenous and non-indigenous people. The headcount ratios for men are systematically above those for the population as a whole, while the ratios for women are systematically below. For both men and women the poverty headcount ratios reached a minimum in 2009, and tended to increase again after that. The gap between women and men, i.e. the absolute difference in their poverty headcount ratios, remains substantial but has varied over time (the gap was 9.94% in 2002 and to 5.74% in 2013). There appears to be a persistent but weakening difference between men and women when it comes to life expectancy-related health poverty. This gap is not due to the fact that women tend to live longer than men, since we correct for that using age and sex specific poverty thresholds. One of the main reasons for the difference lies in the prevalence of smoking. As Table 4 shows, there are huge differences in health poverty rates between smokers and non-smokers. While roughly half of the smoking population lives in health poverty, only one seventh of the non-smoking population does. Moreover, especially since 2009, the poverty headcount ratios for smokers have risen substantially and in 2014 and 2015 were above 60%. As a result, the gap between smokers and non-smokers has widened from 36.38% in 2001 to 46.47% in 2015. For the indigenous population, too, we find health poverty rates which are much higher than those for the rest of the Australian population.

[5] Since the results are very similar for the two health variables and the three poverty measures, we report only the results for the life expectancy headcount ratio P_0. The only exception is the decomposition by sex, where the SF-6D poverty rates are higher for women than for men.

Between 40% and 50% of the indigenous population lives in health poverty, roughly twice the rate of the non-indigenous population. According to our calculations, the gap between the indigenous and non-indigenous population has widened, from 18.07% in 2001 to 28.18% in 2015.

We also looked at the association between health poverty and income. The HILDA dataset provides information on the household income of every individual in every wave of the survey. We transformed household income into equivalized household income by dividing it by a factor depending on the number of adults (a) and the number of children (c) living in the household. The specific formula we used is $1+0.5*(a-1)+0.3*c$. A nice visual representation of the association can be obtained by grouping individuals into quintiles according to the level of their equivalized household income. Figure 4 represents the life expectancy-related poverty headcount ratios for each of the five quintiles, with the first quintile being the poorest and the fifth the richest. The first remarkable observation is that in every year there is a negative social gradient: the higher the income quintile, the lower the poverty headcount ratio. As a result, there exists a wide gap in health poverty between the first and the fifth quintile. Moreover, this gap is widening over time: while the poverty headcount ratio of the fifth quintile has fallen from 13.64% in 2001 to 9.34% in 2015 ($\Delta = -4.31\%$), that of the first quintile has risen from 32.64% to 36.77% ($\Delta = 4.03\%$), with much of the rise occurring after 2009. As a result, the gap between the fifth and the first quintiles has broadened from 18.82% in 2001 to 27.43% in 2015. The first and second quintiles are the only ones for which the poverty headcount ratio has increased over the period 2001-2015, indicating that while life expectancy-related health poverty rates have improved for the population as a whole, this did not happen among those who are income poor. We find similar patterns when looking at health status (Figure 5).

Table 3: Poverty rates in terms of health status (Sf-6D index scores) and Life expectancy for Australia, 2001-2015

	Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
	N	12210	11290	11051	10900	10957	11173	10767	10682	10927	11625	14848	14929	14929	15181	15053
SF-6D Index	P0	35.36	33.53	33.84	33.63	34.45	32.16	32.13	31.71	31.09	33.45	32.95	32.69	33.54	34.64	35.63
	P1	5.09	4.72	4.89	4.76	4.82	4.59	4.55	4.46	4.35	4.75	4.73	4.65	4.77	5.15	5.17
	P2	1.10	0.99	1.04	0.99	1.00	0.98	0.96	0.93	0.90	1.00	1.02	0.98	1.00	1.12	1.12
Life expectancy	P0	22.43	22.70	23.11	23.02	22.55	21.91	21.79	21.00	20.94	22.00	21.24	21.10	21.33	22.30	21.84
	P1	1.20	1.23	1.22	1.22	1.19	1.16	1.14	1.07	1.05	1.17	1.10	1.08	1.12	1.14	1.16
	P2	0.11	0.12	0.11	0.11	0.11	0.11	0.10	0.09	0.09	0.11	0.10	0.10	0.10	0.10	0.11

Source: Own calculations, based on data from the HILDA survey. Figures A1 and A2 of the Appendix provide the 95% confidence intervals around these estimates.

Table 4: Life expectancy poverty headcount ratios in Australia, 2001-2015, by subgroups

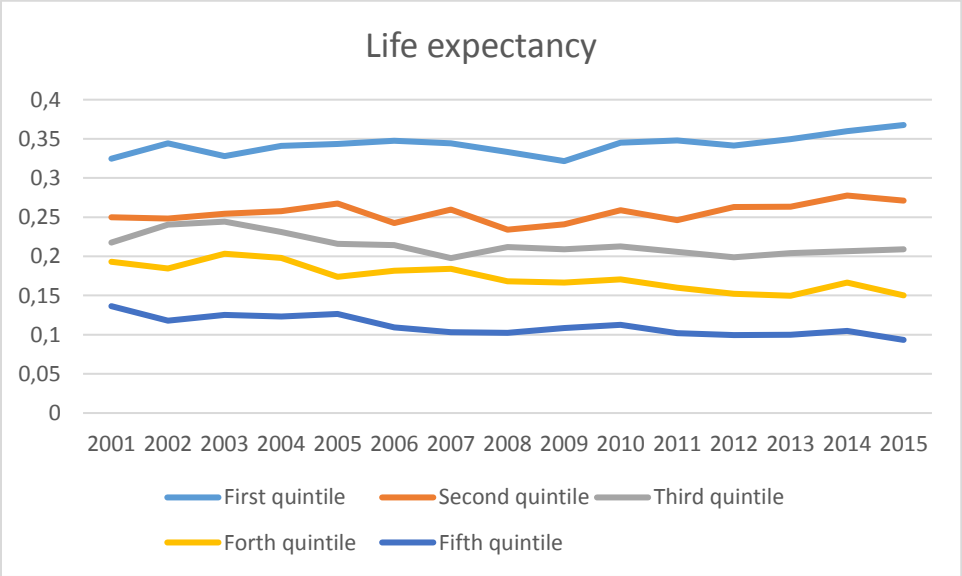
Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Men	27.02%	27.94%	28.07%	27.10%	26.33%	26.15%	25.78%	24.79%	24.40%	25.80%	24.68%	24.49%	24.39%	26.23%	25.74%
Women	18.32%	18.00%	18.70%	19.43%	19.25%	18.20%	18.34%	17.69%	17.89%	18.64%	18.18%	18.15%	18.65%	18.85%	18.39%
Gap	8.70%	9.94%	9.36%	7.67%	7.08%	7.94%	7.44%	7.11%	6.51%	7.16%	6.50%	6.34%	5.74%	7.38%	7.36%
Smokers	50.30%	51.16%	52.85%	53.89%	52.30%	53.51%	52.79%	52.11%	51.53%	54.95%	55.77%	55.96%	58.56%	60.33%	61.03%
Non-smokers	13.92%	14.61%	14.91%	14.75%	14.81%	14.25%	14.37%	13.89%	14.13%	14.77%	14.12%	14.34%	14.27%	14.96%	14.56%
Gap	36.38%	36.55%	37.93%	39.14%	37.49%	39.26%	38.42%	38.22%	37.40%	40.17%	41.66%	41.62%	44.30%	45.38%	46.47%
Indigenous	40.19%	41.36%	40.61%	40.22%	42.49%	42.99%	39.82%	38.39%	39.74%	47.08%	49.54%	46.09%	44.53%	48.98%	49.26%
Non-indigenous	22.12%	22.38%	22.79%	22.73%	22.19%	21.50%	21.41%	20.65%	20.53%	21.44%	20.61%	20.49%	20.74%	21.59%	21.08%
Gap	18.07%	18.98%	17.82%	17.49%	20.29%	21.49%	18.41%	17.74%	19.22%	25.64%	28.93%	25.60%	23.80%	27.39%	28.18%

Source: Own calculations, based on data from the HILDA survey.

Another way of looking at the association between income and health poverty is to calculate aggregate measures of income-related inequality of health poverty. Figure 6 represents the evolution of both the bounded rank-dependent index $R^b(h, g^0)$ (Panel A) and the bounded level-dependent index $L^b(h, g^0)$ (Panel B). As expected, the index values are negative for every wave of the survey, confirming the social gradient visible in the poverty headcount ratios of the income quintiles. Moreover, the index values tend to increase in absolute value over time, albeit not uniformly so, which suggests that socioeconomic inequality of health poverty has worsened over the period 2001-2015. On the whole, the two indices indicate similar trends in inequality.

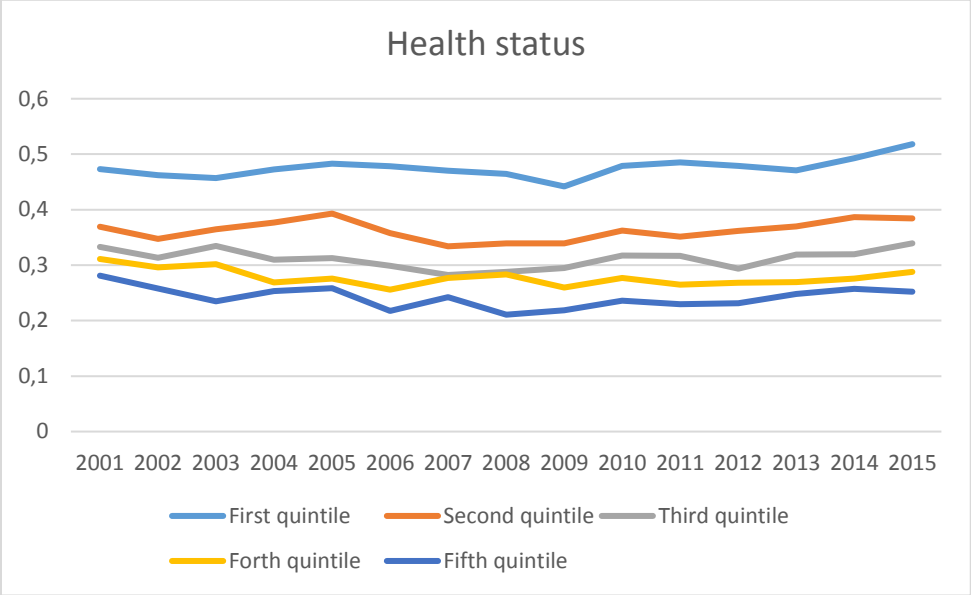
These results are in line with previous research on the relation between income levels and health outcomes in Australia. Based on a simple cross-tabulation of health and poverty status, Buddelmeyer and Cai (2009: 11) have drawn attention to the "clear positive association between ill-health and poverty". Our framework allows a more precise measurement and detailed analysis of the correlation between income and ill-health.

Figure 4: Life expectancy poverty headcount ratios in Australia, 2001-2015, by income quintiles



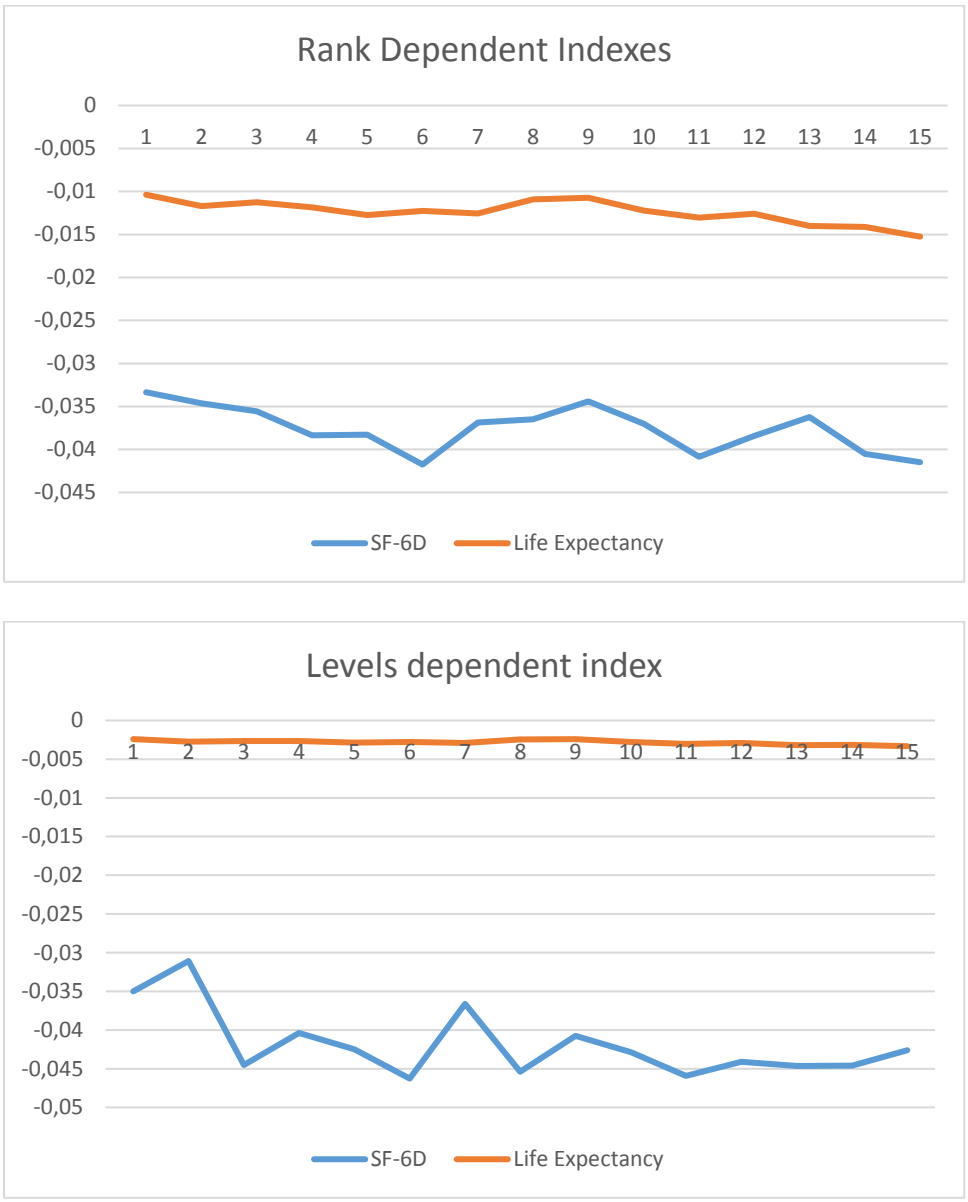
Source: Own calculations, based on data from the HILDA survey.

Figure 5: Quality of life poverty headcount ratios in Australia, 2001-2015, by income quintiles



Source: Own calculations, based on data from the HILDA survey.

Figure 6: Indices of income-related inequality of health poverty in Australia, 2001-2015



Source: Own calculations, based on data from the HILDA survey.

7. Conclusions and future directions

The purpose of this study has been to explore how poverty measures can be used to capture inequalities in health outcomes by revealing to what extent people's health falls below minimally acceptable thresholds. We show that health poverty measures accord closely with widely used practices in medicine to target treatments based on thresholds, such as critical cardiovascular risk levels. Poverty measures also provide a way of systematically quantifying the degree to which a population's health could be improved by treating all persons eligible for treatment (i.e., who are below a threshold).

The dominant approach to measuring health inequalities has been to quantify socio-economic related health inequalities (e.g., the gradient of health outcomes by levels of income) using measures such as the Concentration index. Unlike clinicians that often target treatment using thresholds (e.g., CVD risk), health economists have tended not to focus on the bottom of the health distribution. Our feeling is that poverty measures provide a useful additional set of indices which are likely to have an intuitive appeal among clinicians and policy makers, and which allow economists to draw upon useful properties such as sub-group decomposition. Measuring health poverty is a way of paying more attention to those who are worst off when it comes to health.

As far as the usefulness of health poverty estimates is concerned, there is an obvious connection to the research on the measurement of multidimensional poverty (e.g., Alkire and Santos, 2014). Policy makers may find health poverty calculations useful in order to identify which groups are most disadvantaged in terms of health. However, we do not claim there must be an automatic link between high health poverty rates for certain groups and health policy priorities. Policy makers should also take into account to what extent high levels of health poverty are fair or unfair (cf. the distinction of fair and unfair inequalities in health by Fleurbaey and Schokkaert, 2009).

The systematic measurement of health poverty will require considerable further research. There is scope to apply the health poverty measures developed here much more broadly. Many national health surveys provide information on health status using a generic instrument such as the SF-6D scores of individuals and some provide clinical measures that enable CVD risk to be estimated. Such standard measures of health or illness facilitate comparing poverty rates across countries and over time. To the extent that it is possible to estimate individual life expectancies, there is also room for comparisons of these types of health poverty between

countries and to ultimately to develop measures based on more holistic health measures such as Quality Adjusted Life Years.

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Appendix

Table A1: Summary of sample characteristics of NHANES respondents for two rounds of the survey (2005-2006 and 2013-2014)*

Variable	2005-2006		2013-2014	
	Mean	SD	Mean	SD
Male (proportion)	0.50		0.48	
Age (years)	50.09	12.85	50.80	12.61
Systolic blood pressure (mm Hg)	124.76	18.92	123.93	17.52
Use blood pressure drugs (proportion)	0.26		0.29	
Smoker (proportion)	0.23		0.22	
Diabetes (proportion)	0.12		0.14	
HDL Cholesterol (mg per deciliter)	54.65	16.90	52.75	16.46
Total cholesterol (mg per deciliter)	202.72	42.46	194.11	42.21
Taking a statin (proportion)	0.16		0.20	
Sample size (*n*)	3014		4001	

* Sample weights have not been applied.

Source: NHANES.

Table A2: HILDA variable definitions and descriptive statistics

Variable Definition		Descriptive statistics (Mean (SD))	
Variable	Original HILDA Variable (Description)	Men (*n* = 11,943)	Women (*n* = 12,877)
12 years or greater of education	**edhigh1** (Highest education level achieved)	0.36	0.26
Current smoker	**lssmoke** (Do you smoke tobacco?)	0.25	0.20
Currently married	**mrcurr** (Marital status from person questionnaire)	0.57	0.56
Rural region	**hhsos** (Section of State – rural areas defined as 'Bounded Locality' and 'Rural Balance'	0.15	0.15
Real equivalent household income*	**hifdip** (Household financial year disposable regular income ($) **hifdin** (Household financial year disposable regular income ($) negative values	45.08 (27.09)	43.97 (28.61)
Bodily pain	**ghbp** SF-36 bodily pain – transformed	7.68 (2.36)	7.46 (2.47)
General health	**ghgh** SF-36 general health – transformed	7.12 (2.04)	7.00 (2.10)
Mental Health	**ghmh** SF-36 mental health – transformed	7.51 (1.68)	7.21 (1.78)
Physical functioning	**ghpf** SF-36 physical functioning – transformed	8.56 (2.30)	8.37 (2.32)
Health transitions	**ghrht** SF-36 reported health transitions – raw	2.79 (0.90)	2.80 (0.89)

Role-emotional	**ghre** SF-36 role-emotional – transformed	8.49 (3.08)	8.05 (3.39)
Role-physical	**ghrp** SF-36 role-physical – transformed	8.31 (3.25)	8.06 (3.44)
Social functioning	**ghsf** SF-36 social functioning – transformed	8.39 (2.24)	8.05 (2.38)
SF-6D Health Status Index	**ghsf6d** SF-6D Health state classification	0.77 (0.12)	0.75 (0.12)

* Real disposable equivalent household income has been rescaled by dividing by 1000.

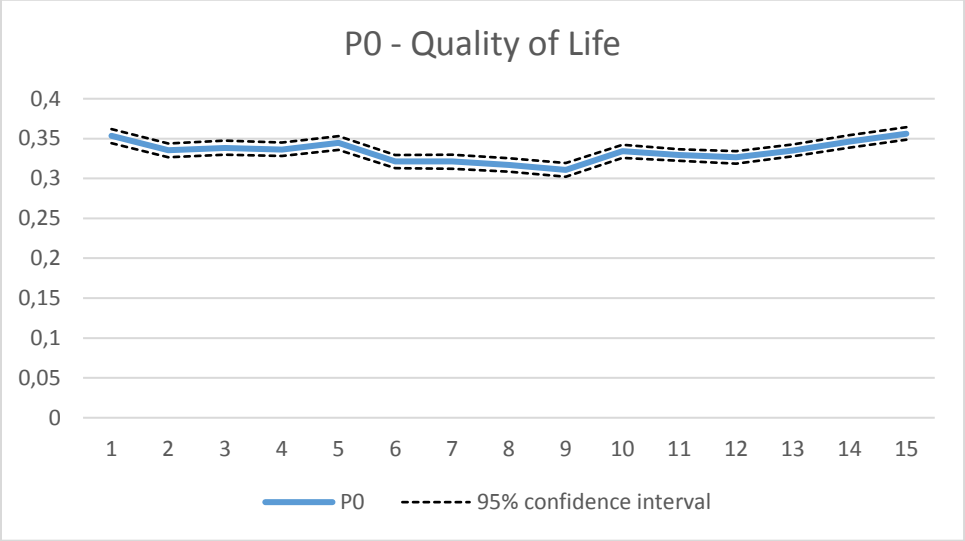
Table A3: A comparison of estimates of expected age at death based on HILDA and those from an Australian life table*

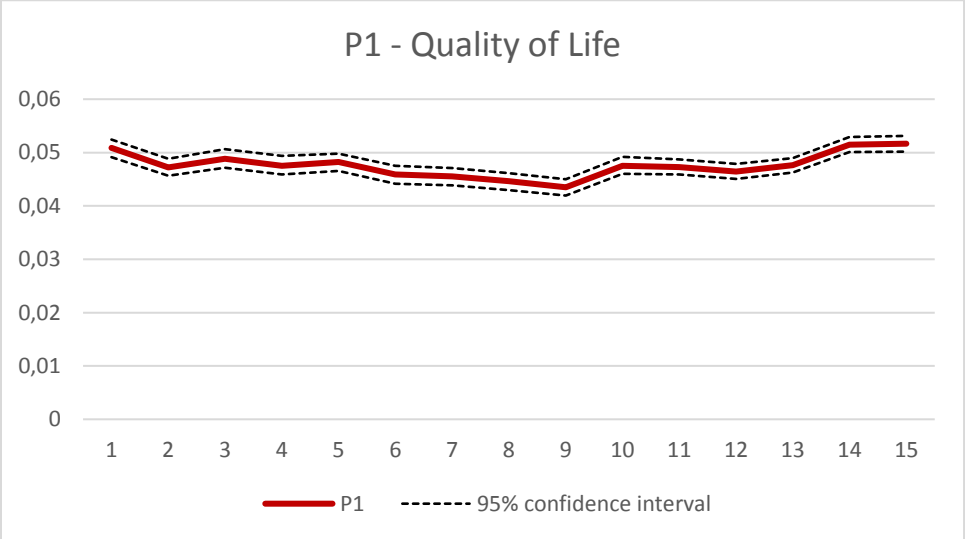
	HILDA Estimates		Life Table		% Diff	
	Females	Males	Females	Males	Females	Males
15	86.1	79.1	84.3	79.9	2%	-1%
16	85.9	78.9	84.4	79.9	2%	-1%
17	85.8	78.7	84.4	79.9	2%	-1%
18	85.7	78.3	84.4	79.9	1%	-2%
19	85.6	78.1	84.4	80	1%	-2%
20	85.7	78.0	84.4	80	2%	-2%
21	85.6	78.4	84.4	80.1	1%	-2%
22	85.6	78.7	84.5	80.1	1%	-2%
23	85.7	78.9	84.5	80.1	1%	-1%
24	85.8	79.3	84.5	80.2	2%	-1%
25	85.8	79.6	84.5	80.2	2%	-1%
26	85.9	79.9	84.5	80.3	2%	-1%
27	86.0	80.0	84.5	80.3	2%	0%
28	86.1	80.2	84.6	80.3	2%	0%
29	86.0	80.5	84.6	80.4	2%	0%
30	86.0	80.6	84.6	80.4	2%	0%
31	86.1	80.8	84.6	80.5	2%	0%
32	86.2	80.9	84.6	80.5	2%	0%
33	86.2	81.0	84.7	80.6	2%	0%
34	86.2	81.1	84.7	80.6	2%	1%
35	86.2	81.1	84.7	80.7	2%	1%
36	86.2	81.1	84.7	80.7	2%	1%
37	86.3	81.2	84.8	80.8	2%	1%
38	86.3	81.2	84.8	80.8	2%	0%
39	86.3	81.2	84.8	80.9	2%	0%
40	86.3	81.3	84.9	81	2%	0%
41	86.4	81.3	84.9	81	2%	0%
42	86.4	81.4	84.9	81.1	2%	0%
43	86.4	81.4	85	81.1	2%	0%
44	86.5	81.5	85	81.2	2%	0%
45	86.5	81.6	85.1	81.3	2%	0%
46	86.5	81.6	85.1	81.3	2%	0%
47	86.6	81.8	85.2	81.4	2%	0%
48	86.6	81.8	85.2	81.5	2%	0%
49	86.7	81.9	85.3	81.6	2%	0%
50	86.8	82.0	85.3	81.7	2%	0%
51	86.8	82.2	85.4	81.8	2%	0%
52	86.9	82.3	85.5	81.9	2%	0%
53	87.0	82.4	85.5	82	2%	0%
54	87.1	82.6	85.6	82.1	2%	1%
55	87.2	82.7	85.7	82.2	2%	1%
56	87.3	82.9	85.8	82.3	2%	1%
57	87.4	83.1	85.9	82.4	2%	1%

58	87.4	83.2	85.9	82.6	2%	1%
59	87.5	83.4	86	82.7	2%	1%
60	87.7	83.6	86.1	82.9	2%	1%
61	87.8	83.8	86.3	83	2%	1%
62	87.9	83.9	86.4	83.2	2%	1%
63	88.1	84.2	86.5	83.4	2%	1%
64	88.2	84.3	86.6	83.5	2%	1%
65	88.4	84.6	86.8	83.7	2%	1%
66	88.5	84.8	86.9	84	2%	1%
67	88.7	85.0	87	84.2	2%	1%
68	88.8	85.2	87.2	84.4	2%	1%
69	89.0	85.4	87.4	84.7	2%	1%
70	89.2	85.7	87.5	84.9	2%	1%
71	89.4	85.9	87.7	85.2	2%	1%
72	89.6	86.2	87.9	85.5	2%	1%
73	89.8	86.6	88.1	85.8	2%	1%
74	90.0	86.8	88.4	86.1	2%	1%
75	90.3	87.3	88.6	86.4	2%	1%
76	90.5	87.6	88.8	86.8	2%	1%
77	90.8	88.0	89.1	87.1	2%	1%
78	91.1	88.4	89.4	87.5	2%	1%
79	91.4	88.6	89.7	88	2%	1%
80	91.6	89.1	90	88.4	2%	1%
81	92.0	89.6	90.4	88.9	2%	1%
82	92.4	90.0	90.8	89.4	2%	1%
83	92.8	90.3	91.2	89.9	2%	0%
84	93.1	90.9	91.6	90.4	2%	1%
85	93.5	91.5	92.1	91	1%	1%
86	93.9	91.9	92.6	91.6	1%	0%
87	94.4	92.3	93.1	92.2	1%	0%
88	94.9	92.8	93.6	92.9	1%	0%
89	95.4	93.3	94.2	93.5	1%	0%
90	96.0	93.9	94.8	94.2	1%	0%
91	96.5	94.6	95.5	94.9	1%	0%
92	97.0	95.0	96.1	95.7	1%	-1%
93	97.7	95.7	96.9	96.5	1%	-1%
94	98.2	96.5	97.6	97.3	1%	-1%
95	98.8	97.3	98.4	98.1	0%	-1%

* The published life table estimates are based on Australian Bureau of Statistics Life Tables, Australia, 2007-2009, 2010 Catalogue No. 3302.0.55.001. We chose these life tables as a comparator as they are at mid-point of the period covered by the HILDA study.

Figure A1: Graphs reporting the 95% confidence intervals of the poverty estimates of Table 3 (SF-6D Index)





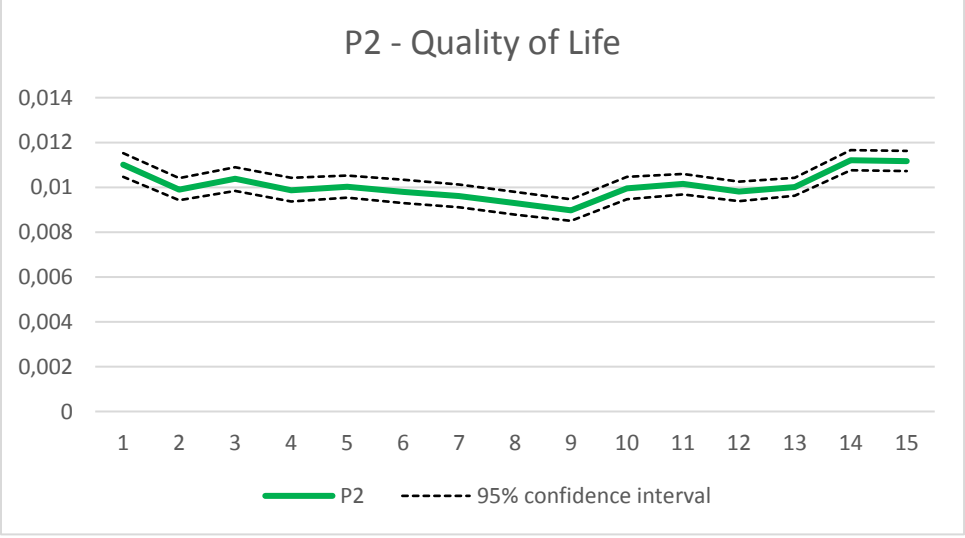


Figure A2: Graphs reporting the 95% confidence intervals of the poverty estimates of Table 3 (Life expectancy)