REAL Centre Working paper

A microsimulation model for multimorbidity in England

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The Health Foundation

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1 Introduction

Designing and delivering a health service fit for the needs of the future requires planning. The workforce needs to be trained, the physical infrastructure needs to be built and capital needs to be invested. These processes take time; the training of staff and investment in appropriate capital can take years. Therefore, policymakers must have, well in advance, a clear understanding of the future demand for health care. Projections of patterns of population ill health play a crucial role in understanding future health care demand. The Health Foundation's REAL Centre (Research and Economic Analysis for the Long term) has been producing projections for health care resourcing and funding for several years, the most recent of which were published in 2021 (1). However, the availability of new linked data and the development of new methods have created an opportunity to markedly improve the quality of the projections.

We have partnered with the University of Liverpool's Department of Public Health, Policy and Systems, part of the Institute of Population Health, to provide a more robust epidemiological framework to estimate illness with the help of a microsimulation model. In this partnership we build on the IMPACT$_{NCD}$ model structure originally developed by Chris Kypridemos and team over the last 10 years. This model uses patient-level linked health and mortality data, epidemiological research and survey responses on individual-level risk factors to create a synthetic population representative of England from 2013 to 2019. Following econometrically generated trends in illness incidence, remission and mortality rates, with assumptions about the relationship between illnesses and their causes, the model projects this population into the future. The synthetic population lives out the next 20 years of their lives to 2040, developing further illness or dying with probabilities generated from the data. The resulting output is a projection of the population in England to 2040, with estimated age, size and levels of illness and multimorbidity.

The projections from this model will improve upon the current estimates in two respects:

- A microsimulation structure enables modelling at the individual level rather than for population groups, which enables projecting illness at a more granular level.
- We use linked primary and secondary care data rather than secondary care data alone (as we did for previous versions) to estimate illness levels. This will provide greater insight into individuals' illness histories such as individuals with well-managed chronic conditions who have not used secondary care.

This model will provide the basis for a series of reports focused on the future demand pressures on the health service. Through this programme we build a picture of the underlying levels of health and social care demand, health inequality and the expected changes in needs as our population grows and continues to age. In this working paper we provide a conceptual framework for and structure of the model, a summary of its

internal workings, the key assumptions and input data involved, and the model outputs and how they are estimated. Additional detail is provided in the technical appendix to the projections report, *Health in 2040: projected patterns of illness in England*.

We begin, in the next section, with the conceptual framework underpinning the model and its structure. In the following sections, we break down the framework into its component parts and describe how they are incorporated in the model and any assumptions involved. In section 3 we describe the first component of the framework, ie the wider determinants of health. In section 4 we describe the behavioural and biological risk factors included in the model, their projected trends and their relationships with the modelled illnesses as estimated using epidemiological research. In sections 5 and 6 we describe the trends and assumptions regarding incidence and mortality. The key determinants of illness in the population are the rates of incidence, rates of remission (for some conditions) and the rates of mortality for people with illness at different ages. These factors ultimately determine the prevalence of illness and multimorbidity in the population. This dynamic relationship between incidence, mortality (and remission) and prevalence is described in more detail in section 7. In the final section (8) we describe our key metrics of ill health such as the Cambridge Multimorbidity Score (CMS) and life expectancy spent in different states of illness, how they are calculated and the assumptions involved.

2 Conceptual framework and model structure

2.1 Conceptual framework

The model is grounded in epidemiological principles based on the relationship between risk factors, the onset of illness and mortality. The model uses estimates from peer-reviewed literature on the causal associations between risk factors and illness incidence and mortality. Figure 2.1 below shows a conceptual framework for the determinants of illness.

Figure 2.1: Conceptual framework of the model showing the relationship between ill health and its determinants
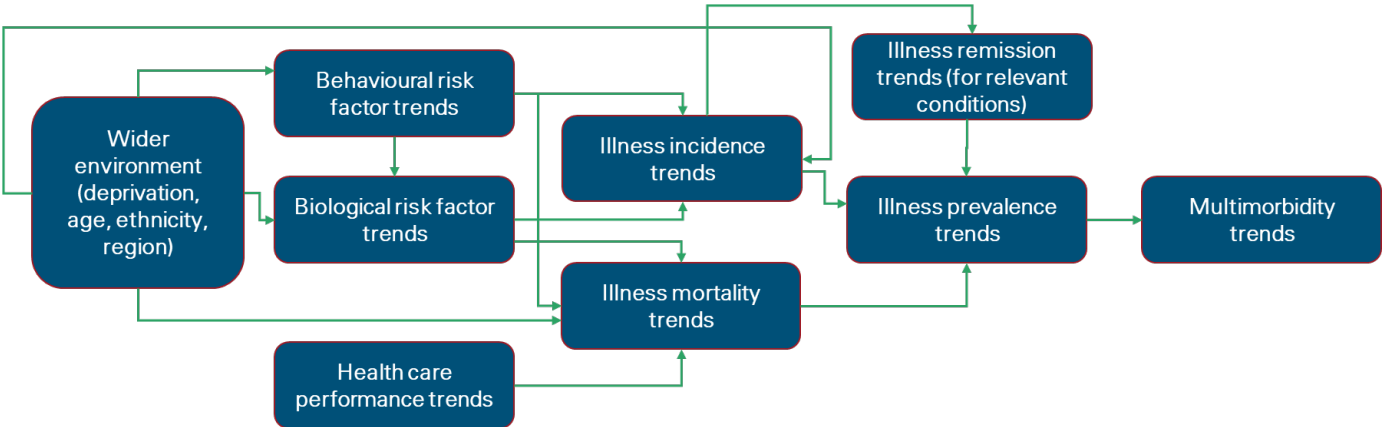
Source: Authors' representation.

Based on this framework, an individual's behavioural risk factors (eg smoking or exercise) depend on their sociodemographic characteristics (eg age, sex and area-level deprivation). These both then affect the level of biological risk factors (eg blood pressure). Incidence of a given condition then depends on these biological and behavioural risk factors and sociodemographic characteristics, as well as diagnosis of other conditions. In addition to the same parameters that affect incidence, mortality is also dependent on how conditions are managed and treated by the health care system. We also assume the possibility of remission for some of our conditions which depends on individuals' sociodemographic characteristics. Incidence, mortality and remission (where relevant) together determine prevalence (the number of people with illness at a given time). We then use prevalence to show aggregate measures of population ill health such as overall life expectancy, life expectancy spent in different states of illness and multimorbidity (the presence of multiple illnesses).

2.2 Model structure

The first step in the modelling is to create a population (aged 30 years and older) that is representative of England in 2013 (the first year of every simulation in the model). The inputs for population characteristics such as age, sex, ethnicity, region and decile of deprivation are drawn from ONS population estimates and the 2011 Census (2). Conditional on these characteristics, initial levels of ill health as well as projections of

future incidence and mortality are estimated using a 1.7 million person sample[*] from the Clinical Practice Research Datalink (CPRD) linked to Hospital Episode Statistics (HES) and Office for National Statistics (ONS) mortality data. These administrative primary and secondary care records contain information on diagnoses as well as patients' demographic information, therefore allowing us to estimate illness prevalence, incidence and case fatality. These estimates act as inputs to the model. The synthetic population sample size is 200,000 at the beginning of the simulation, which is then weighted to the full population of England for presentation.

Using this representative population, we then project longevity and health in England: the onset of 20 chronic conditions and of death is then 'simulated' for each subsequent year. This means that in each simulated year, the model assigns conditions to each simulated individual and determines whether they die. Those simulated individuals who die leave the simulation for all future periods. The onset of illness and death occur with a probability that depends upon a combination of patient-level characteristics (age, sex, region, ethnicity, deciles of local area deprivation, past exposures to relevant risk factors and other pre-existing diagnosed illness). These probabilities are derived from the patient-level health data, mortality records, their assigned biological and behavioural risk factors based on the Health Survey for England series (HSE), and epidemiological evidence on risk factors. These individual-level health changes are aggregated or summed up to form the basis of our projections.

Further details of the methodology are provided in the technical appendix. The remainder of this paper describes the different components of the conceptual framework and how they are included in the model.

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[*] The final sample size is 1,655k after exclusions. More detail on our sample exclusion criteria can be found in the technical appendix.

3 Wider determinants of health

The wider determinants of health are well known and summarised in a rainbow graph by Dahlgren et al (3), which illustrates all the major determinants of health in a hierarchical manner (Figure 3.1). The key message of the graph is that every layer influences its inner layers and is influenced by its outer layers. In the innermost central circle are individuals with their biological traits. Many of the traits cannot be changed, like age or genetic make-up. Nevertheless, some individual factors, such as systolic blood pressure or cholesterol, can be influenced by the outer layers. The next layer consists of individual lifestyle factors, ie the behaviours adopted by individuals such as smoking or an unhealthy diet. These behaviours both influence the central circle and are influenced by the outer layers and the pattern goes on. The overall health of individuals is therefore determined by the interplay between all the different determinants at the macro and micro levels throughout the life course.

Figure 3.1: The social determinants of health rainbow
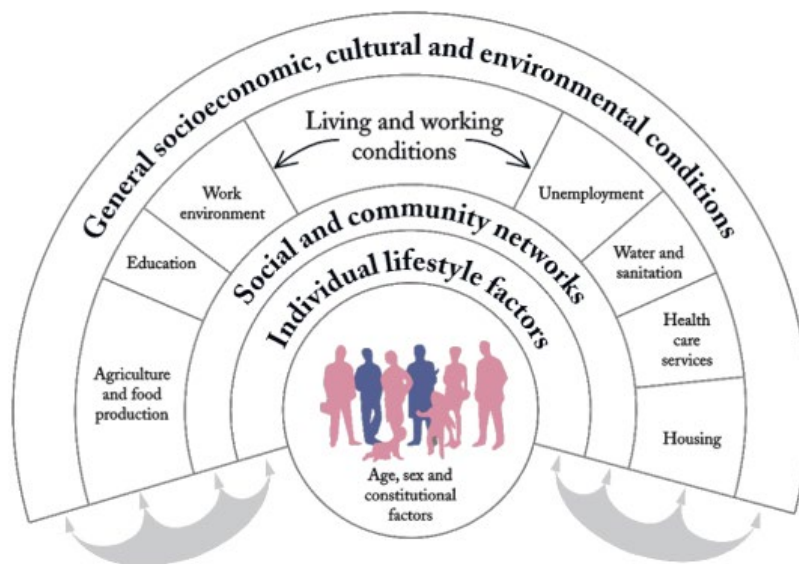
Source: Adapted from Dahlgren et al. (3).

Figure 3.2 describes how this health rainbow relates to our model. Information on demographic characteristics such as age, sex, ethnicity, region and Index of Multiple Deprivation (IMD) decile come from administrative primary care records. Information on risk factors comes from the Health Survey for England (HSE). These are statistically 'matched' to our modelled population based on those personal characteristics, ie smoking rates for 30-year-old white men in the deprived parts of the North of England will be higher than the smoking rates for the same group in the affluent areas as reflected in the survey data. Using evidence from the literature on the link between smoking and cancer, we will then expect to have higher incidence of lung cancer in more deprived areas. These known epidemiological relationships between *some* of the known individual risk factors and incidence of illness then inform our modelling of the future of chronic illness.

Figure 3.2: How we model the social determinants of health rainbow – amended for data availability
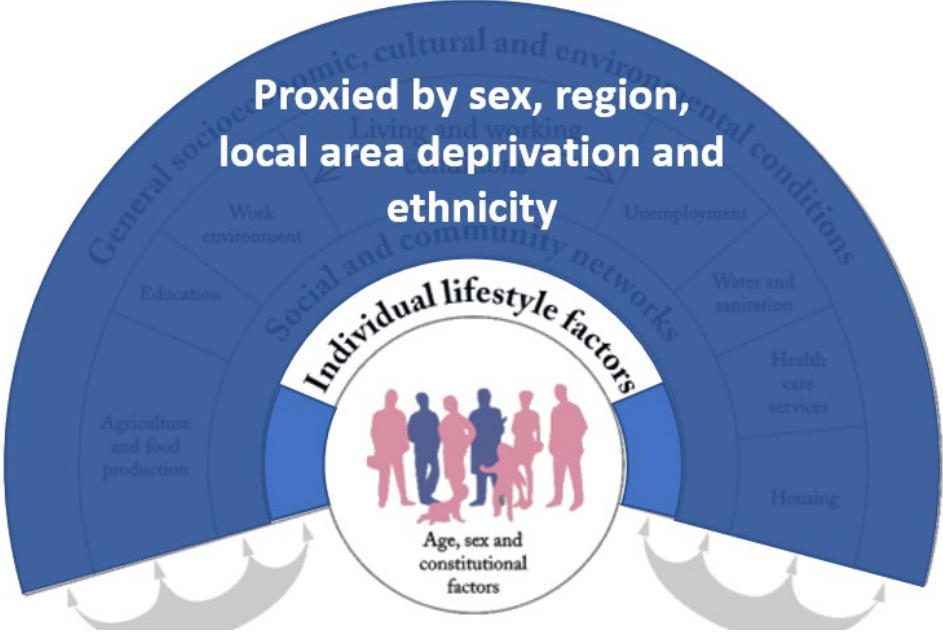
Source: Authors' representation.

The outer layers are all proxied by an individual's region, IMD decile, sex and ethnicity, reflecting data limitations. However, it is important to note that there are serious methodological challenges in isolating the causal effect between a single factor in one of the outer circles and health, as they are so interrelated. Improved observational data would not address all these challenges.

It is important to note that there is substantial variation in health across the population, which is not explained by age, our measured risk factors, or the factors we use to proxy the outer layers.

4 Risk factors and incidence of illness

4.1 Measuring risk factors

The next step in the model framework after the wider determinants of health involves the behavioural and biological risk factors. In our model, the data for this come from the Health Survey for England (HSE). The risk factors, described in Table 4.1, are then statistically 'matched' to our modelled population. This matching is based on year, region, sex, age, IMD decile and ethnicity. This means, for example, that all white men aged 35 years living in the most deprived decile in the north-east of England in 2013 in the modelled population will be assigned a rate of smoking found for the same group in HSE.[*]

Table 4.1: Major risk factors included in the microsimulation model

Risk factor		Measurement
Active days		Days per week
Alcohol consumption		Grams per day
Fruit consumption		Grams (80g is 1 portion)
Vegetable consumption		Grams (80g is 1 portion)
Smoking	People who are active smokers	Share
	Average daily consumption	Number of cigarettes
Body mass index (BMI)		kg/m²
Systolic blood pressure		mmHg
Total cholesterol		mmol/litre

Source: Health Survey for England (HSE)

Note: The model calculates exposure to smoking using a variety of metrics including smoking duration, exposure to passive smoking and how long people who quit smoking remain abstinent. We present here only the proportion of people who are active smokers and the average daily cigarette consumption for simplicity. For more detail on the other metrics that are used to calculate smoking exposure, please refer to the technical appendix.

4.2 Trends in risk factors

Our analysis follows trends in self-reported individual-level risk factors reported in the Health Survey for England (HSE) and projects them up to 2040. We assume them to follow a log-linear trend as it was found to better fit the data. The team that developed the IMPACT$_{NCD}$ model has used the same assumption across multiple previous

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[*] For example, if 10% of a particular population subgroup smoke in a given year, out of 100 people in this group in the simulated population 10 are chosen to smoke at random.

applications of the model that have been published extensively (4–8). The use of HSE data from 2013 onwards drives the projected trend in future risk factors for the population in our model. This decision was taken for several reasons, but most importantly it was due to the consistent recording of risk factors based on age, sex, decile of IMD, ethnicity and geographic region over time. This allows us to separately model the projected incidence of long-term illness for different population subgroups. The assumed log-linear trend in risk factors will also have a bearing on the results of the model, ie this would serve to temper the projected trends in risk factors in contrast to an assumption of linearity.

Recent trends for some risk factors have shown a gradual improvement. Fewer people were smoking in 2019 than in 2013 and those that did smoke tended to smoke less, self-reported alcohol consumption on average fell slightly, while the average reported level of physical activity rose slightly. BMI has shown no signs of improving and is projected to increase in the future. Projected trends in all modelled risk factors are shown in Figures 4.1a and 4.1b.

Figure 4.1a: Trends in helpful risk factors for those aged 30 years and older, 2003–2040 (projected), standardised for age, sex and deprivation
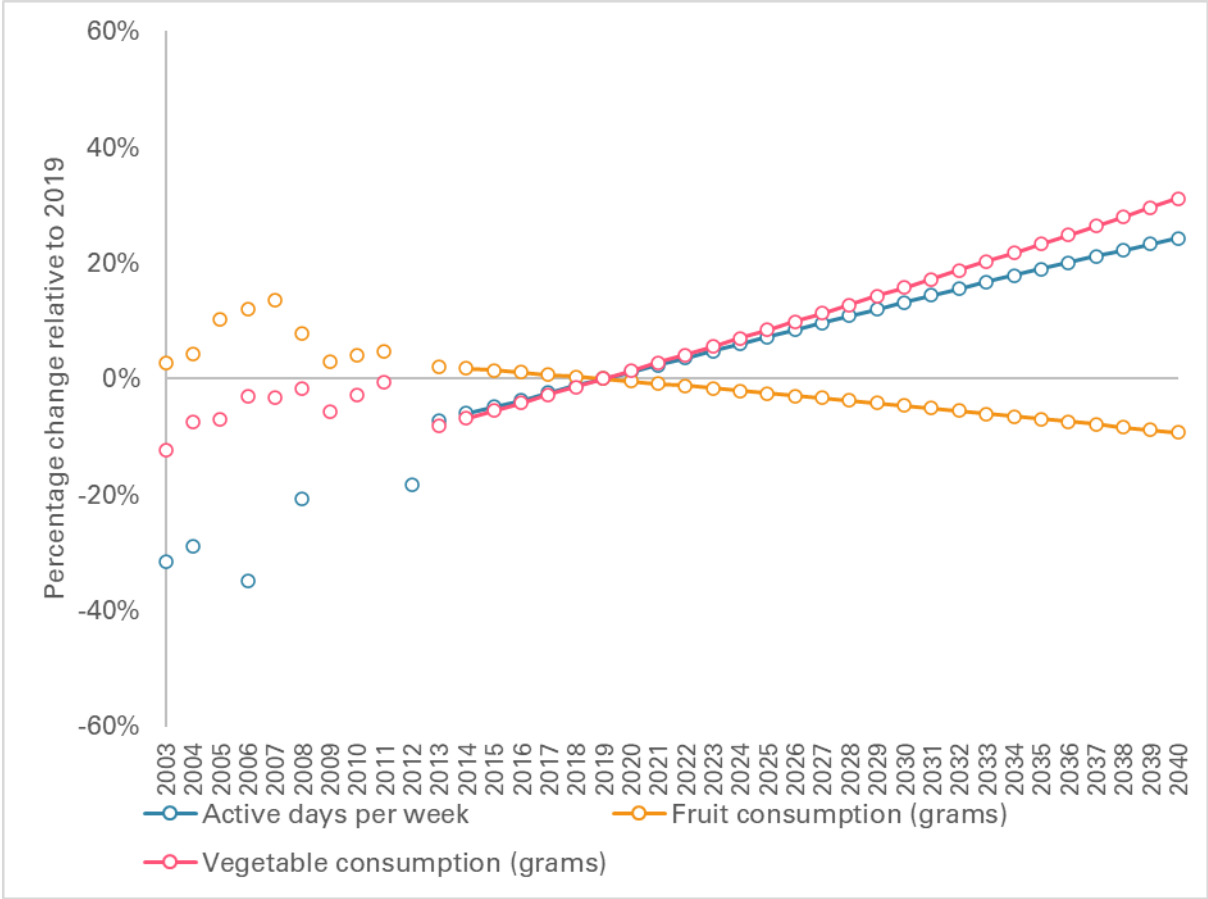
Source: Health Survey for England (HSE) for the years 2003 to 2012 and calculations by the University of Liverpool for subsequent years.

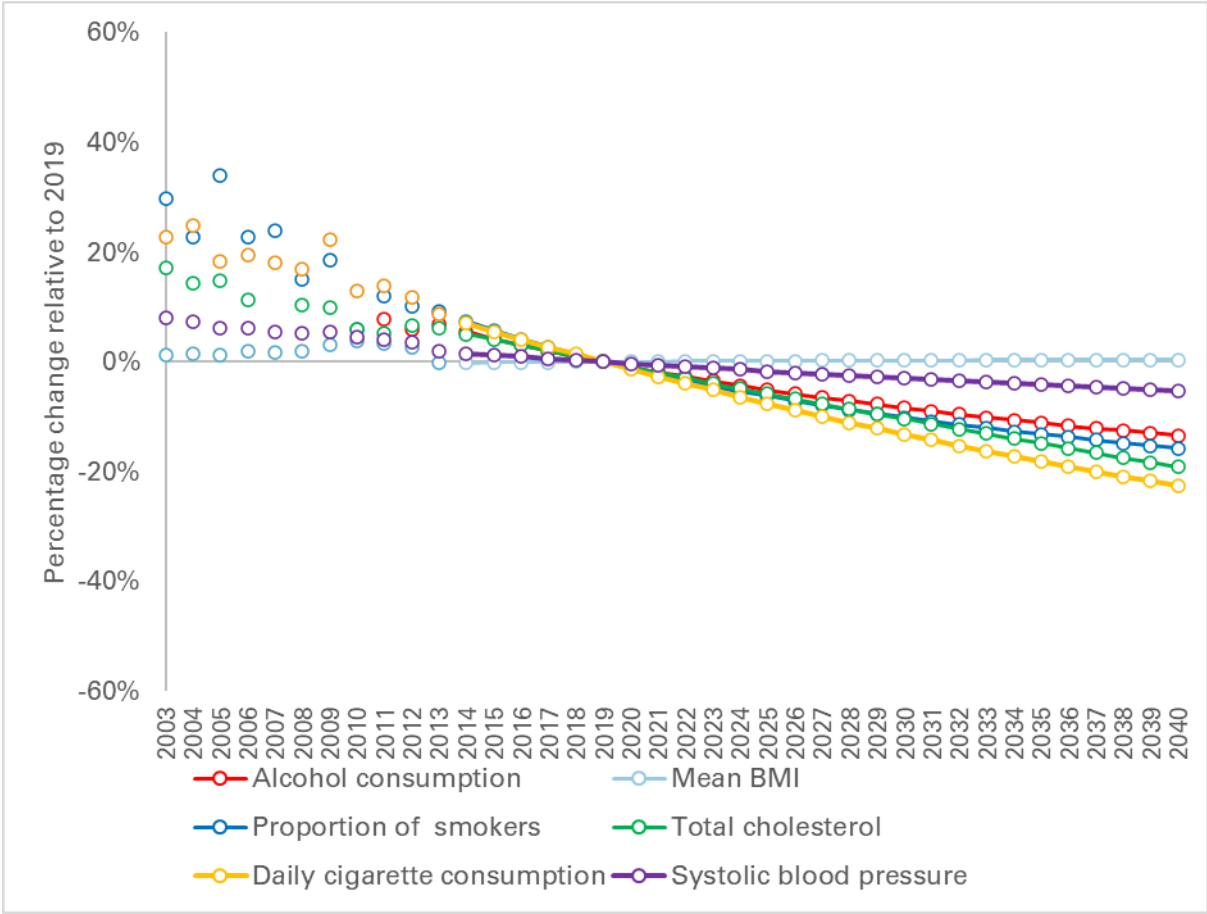**Note**: Due to changes to the survey, some variables might have missing values between 2003 and 2012.

Figure 4.1b: Trends in harmful risk factors for those aged 30 years and older, 2003–2040 (projected), standardised for age, sex and deprivation

Source: Health Survey for England (HSE) for the years 2003 to 2012 and calculations by the University of Liverpool for subsequent years.

Note: Due to changes to the survey, some variables might have missing values between 2003 and 2012.

Our projections in *Health in 2040: projected patterns of illness in England* assume that these risk factors continue to follow past trends. We follow regression models with a log-linear functional form. The choice of the form is data driven, ie selected to best fit the existing trends in the data, and we ensured that they are within plausible (ie biologically compatible) boundaries. These regressions give trends that are maintained into the future based on population characteristics from the HSE, including age, sex, ethnicity and deprivation. Further details are provided in the technical appendix section 2. We project an increase in projected BMI and a fall in fruit consumption. Vegetable consumption and the number of active days in the population, on average, are projected to increase by 31% and 24% respectively, with total cholesterol, systolic blood pressure, proportion of smokers, daily cigarette consumption and alcohol consumption projected to reduce, on average, between 2019 and 2040. The projections are subject to the assumed log-linear trends; an alternative assumption of linearity would change these. The chosen methods for projection of risk factors have been widely peer reviewed (9–13).

BMI is projected to increase by 0.4% when we standardise for age, sex and deprivation. The projected trend in BMI means that the prevalence of obesity (BMI equal to or greater than 30kg/m^2) for those aged 30 years and older (excluding the very old) is projected to increase from 25% to 26% between 2019 and 2040. But this hides variation in trends by age as Figure 4.2 shows.

Figure 4.2: Obesity prevalence by age group, 2019 and projected for 2040
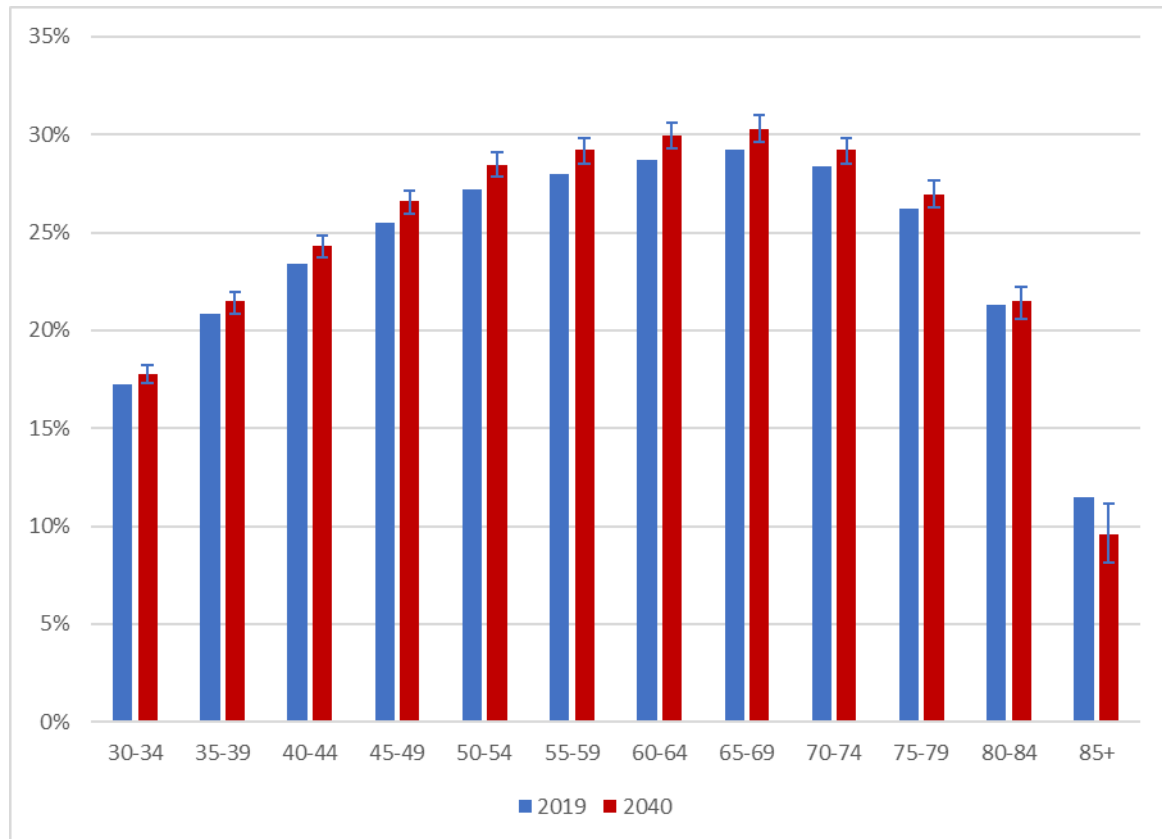
Source: Analysis by the University of Liverpool.

Note: The capped bars represent uncertainty intervals.

All age groups except those aged 85 years and older are projected to see a small increase in obesity prevalence between 2019 and 2040.[*] Just under a third of all individuals (29%) aged between 50 and 74 years are projected to be obese in 2040.

The projected flattening of overall obesity indicates a markedly different trend compared to the rapid growth seen in the past. Between 1993 and 2019 the share of the adult population living with obesity almost doubled (15% to 28%) (14). The number who are overweight or obese grew from 53% to 64% in the same period. These are

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[*] This is probably the result of sarcopenia which is a condition that causes age-related progressive loss of muscle mass and strength that affects the very old (49).

dramatic changes, caused by fundamental shifts in food environments over that period. These changes will be very difficult to reverse.

The trends from the 1990s and 2000s represented a big shift in the prevalence of obesity. Many of the changes to the economy, lifestyles and food environments that have contributed to the creation of an 'obesogenic' environment in England happened during that time. These include improvements in the affordability and availability of calorie-dense foods, large portion sizes and particularly the frequency with which people eat out-of-home meals (15). If the causes of obesity, such as food environments, do not worsen in the coming years then it is possible that we do not see dramatic further increases in the prevalence of obesity.

Importantly for our modelling, a stabilisation in rates of obesity does not mean that the impact of obesity on growing illness prevalence has steadied. This is because the lifetime risk of developing conditions increases with the number of years a person has been obese. People who are obese at the age of 60 in 2019 will have been 31 in 1990 and have lived through the step change in obesity. People who are 60 years old in 2040 may well be as likely to be obese as those in 2019, but will, on average, have been obese for longer. In terms of lifetime risk of illness, the length of time a person lives with obesity is a key factor. The importance of prolonged exposure to obesity (and other risk factors) is included in the model because a person's lifetime risk of developing a health problem is cumulative, ie the probability that an obese 60-year-old has an associated health problem is projected to be higher in 2040 than in 2019 because they are projected to have had greater risk exposure throughout their adult lives.[*]

This concern can be further illustrated by the worrying growth in childhood obesity. In 2021/22 the Office for Health Improvement and Disparities (OHID) data showed that 10.1% of 4–5-year-olds and 23.4% of 10–11-year-olds were obese (16). This denotes an increase on pre-pandemic levels (2019/20), when 9.9% of children aged 4–5 years and 21.0% of children aged 10–11 years were obese. We know that obese children are five times more likely to become obese adults (17) and the statistics are strongly associated with inequalities, with children in deprived areas around twice as likely to be living with obesity (18). These trends are worrying and create a lot of uncertainty for the future of population health in the current cohort of children.

For other risk factors, the improvements found in the Health Survey for England (HSE) since 2003 also mask longer term worsening in exposure to risk factors, as noted in Everest et al. (2022) (19). Public Health England (now OHID), states that levels of physical activity are 20% lower now than they were in the 1960s (20). In terms of diet,

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[*] In a given year, living with obesity increases the risk of developing illness. However, whether the risk for a single year is affected by the longevity with exposure is not well understood. This is because the future effects of persistent obesity on elevated risk would require longitudinal research linking risk exposure to disease incidence. Currently, our model does not consider the length of time someone spends with obesity in determining health outcomes in an individual year; we therefore note that our analysis could be missing the full health consequences of the obesity epidemic on health and multimorbidity in England.

fruit and vegetable consumption has been consistently low over the past decade, particularly among those living in the most deprived areas (21,22). In 2018, fewer than 3 in 10 adults in England ate the recommended five portions a day (23). The UK population consumes more highly processed food than any other European country (24–26). The projected improvement in some of the risk factors used in our modelling comes from a low base.

Alcohol consumption can negatively impact nearly every organ in the body and harmful use causes life-threatening illness such as liver disease and mental health problems.[*] The levels of self-reported alcohol consumption from HSE show a reduction for many people in units over time on average. They also show higher levels of average consumption of alcohol in more affluent areas than in more deprived areas. Although the highest fifth of earners are the most likely to drink over the recommended amount (23), alcohol-attributable hospital admissions and deaths are significantly higher for adults living in the most deprived areas (27,28). Possible explanations include the presence of multiple risk factors, more high-risk drinking behaviours such as binge drinking, and poorer access to alcohol treatment and support in more deprived areas (29,30).

4.3 Individual-level risk factors and incidence of illness

The model only includes risk factors that are causally linked to long-term illness in the epidemiological literature.[†] Table 4.2 below shows which of our risk factors are linked to which conditions. There are several other conditions, such as chronic pain, anxiety and depression, and irritable bowel syndrome (IBS) for which there is no or limited scientific evidence that quantifies a causal link between our modelled risk factors and incidence. Incidence of these conditions is modelled using patient-level characteristics of age, IMD decile, region, sex and ethnicity. It will also be affected by the conditions an individual is diagnosed with.

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[*] As included in our definition of 'Alcohol problems' in the primary care data.

† The full list of the literature used can be found in the technical appendix.

Table 4.2: Risk factors and their associations with conditions

	Breast cancer	CHD	Colorectal cancer	Stroke	AF	Type 2 diabetes	Asthma	CKD	Dementia	COPD	Lung cancer	Prostate cancer
Physical activity	X	X	X	X		X						
Alcohol	X	X	X	X	X	X						
BMI	X	X	X	X	X	X	X	X	X			
ETS (second-hand smoke)	X	X		X		X					X	X
Fruit intake		X		X		X						X
Systolic blood pressure		X		X	X			X				
Smoking	X	X	X	X	X	X	X		X	X	X	X
Cholesterol		X		X								
Vegetable intake		X		X								

Source: Analysis by the University of Liverpool. For the full list of papers linking risk factors to conditions, please refer to the technical appendix.

Notes: BMI stands for body mass index; CHD is coronary heart disease; AF is atrial fibrillation; CKD is chronic kidney disease; COPD is chronic obstructive pulmonary disease.

Figure 4.3 below shows the population attributable risk fraction (PARF) for the 20 Cambridge Multimorbidity Score (CMS) conditions[*] which gives the share of incidence that can be explained by major risk factors using evidence from the epidemiological literature. It also shows the share of incidence that is modelled using patient-level characteristics and the presence of other conditions. The greatest proportion of incident cases that are explained by major risk factors are for type 2 diabetes, lung cancer and coronary heart disease (CHD), at two-thirds or more.

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[*] Please refer to Table 8.1 for the full list of the 20 CMS conditions.

Figure 4.3: Population attributable risk fraction (PARF) analysis for all CMS conditions for those aged 30 years and older, non-standardised (%)
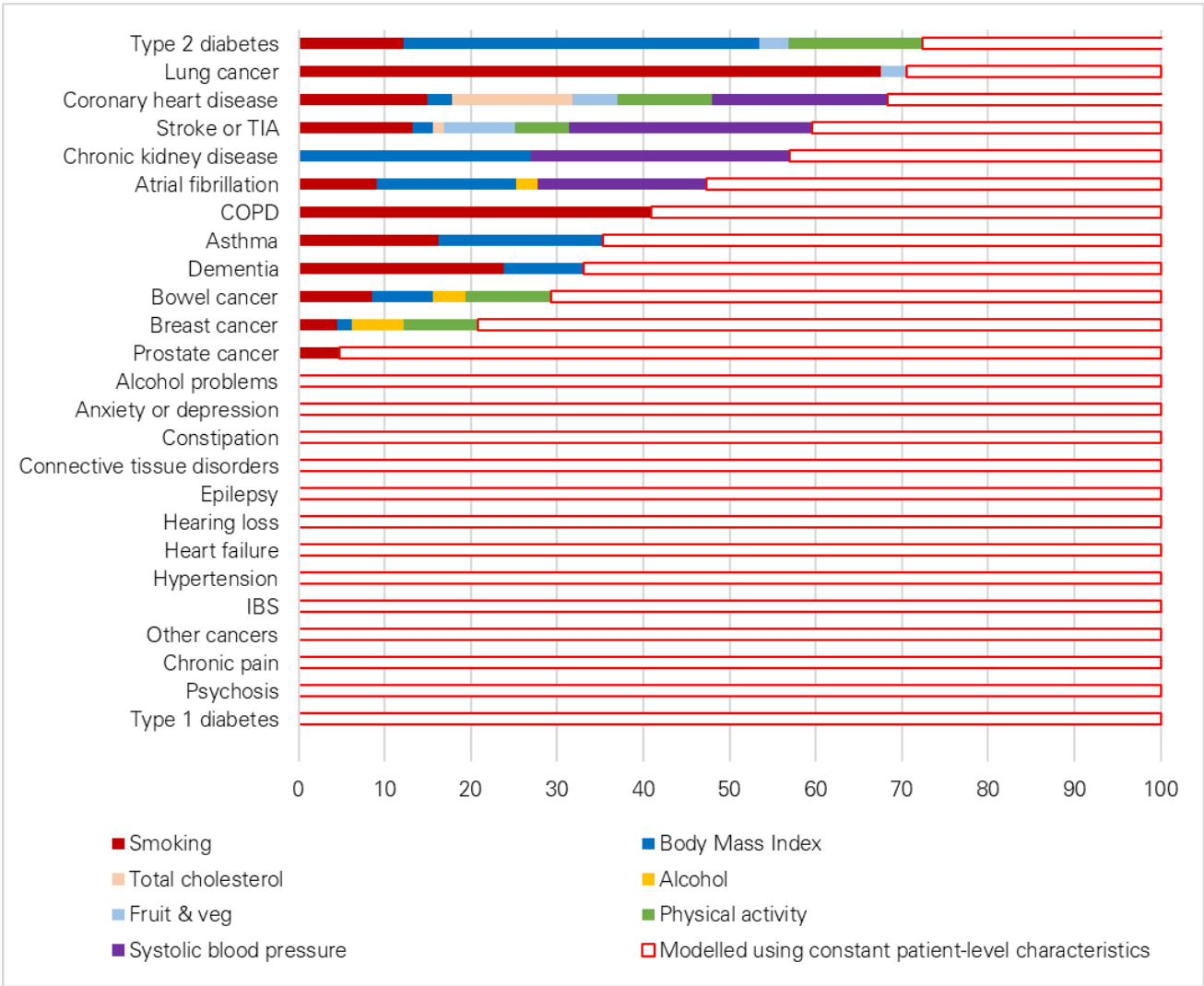
Source: Analysis by the University of Liverpool.

Note: TIA is transient ischaemic attack, COPD is chronic obstructive pulmonary disease, IBS is irritable bowel syndrome. The model includes a lag between exposure to a given risk factor and onset of illness. The lags are, on average, 4 years for CHD and stroke, 5 years for COPD, asthma and type 2 diabetes, and 9 years for dementia and all cancers.

There are many wider determinants of health that we cannot model directly, so only a portion of the projected cases of illness are determined by the modelled risk factors. The remaining cases follow trends in incidence based on people's sociodemographic characteristics.

5 Incidence

Through the causal quantified relationships in the previous section, we observe changes in the incidence rates of some of the conditions in the model. The effect on incidence is summarised in Figure 5.1 below. More detail on the extent of the determinants of incidence in individual-level risk factors is presented in the technical appendix.

Figure 5.1 shows the projected percentage point changes in incidence rates for all conditions between 2019 and 2040. All conditions except asthma and coronary heart disease (CHD) are projected to have very small changes to incidence rates between 2019 and 2040. The reduction for coronary heart disease and other lung and cardiovascular conditions such as stroke, chronic obstructive pulmonary disease (COPD) and atrial fibrillation (AF) is likely related to risk factors that are improving such as smoking.

Figure 5.1: Projected percentage point changes in incidence rates by condition for those aged 30 years and older between 2019 and 2040, England, standardised for age, sex and deprivation
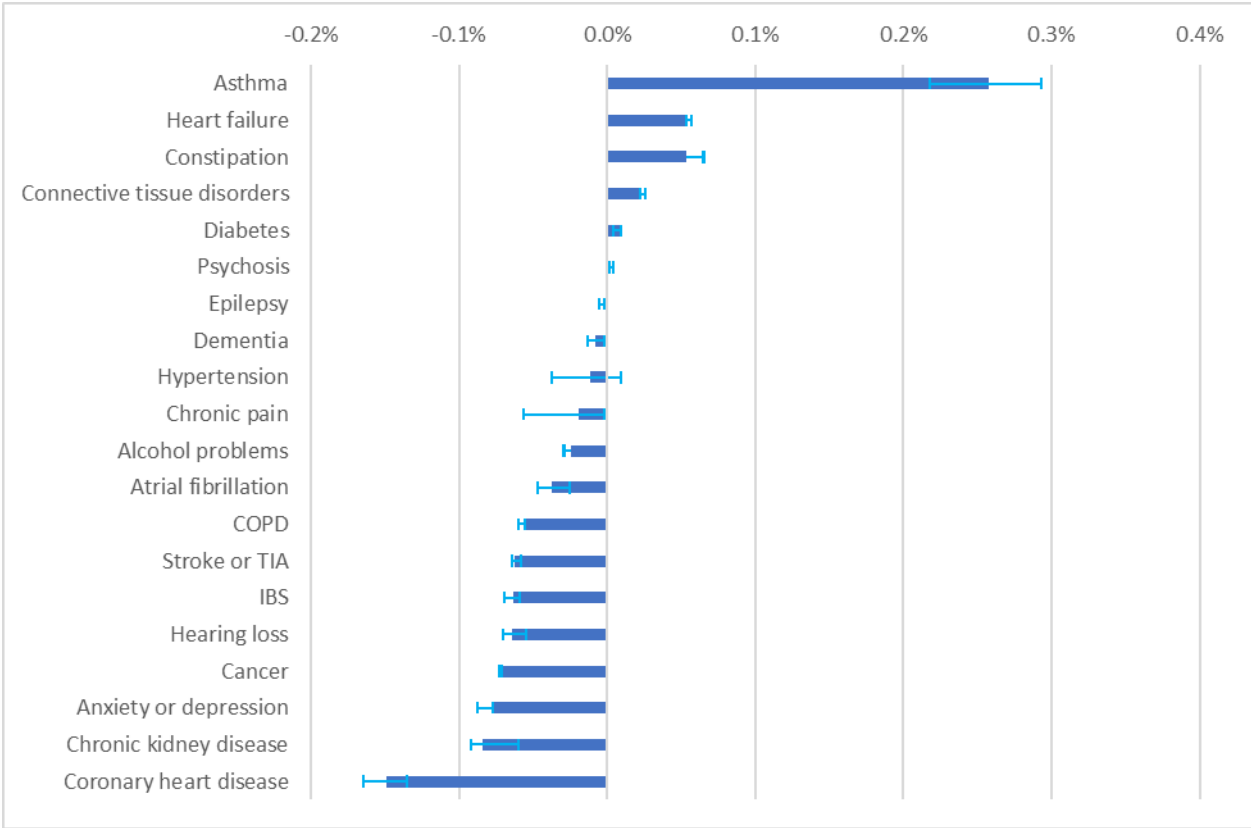
Source: Analysis of linked health care records and mortality data conducted by the REAL Centre and the University of Liverpool.

Note: The capped bars represent uncertainty intervals. COPD is chronic obstructive pulmonary disease, TIA is transient ischaemic attack, IBS is irritable bowel syndrome.

6 Mortality

Each member of the modelled population is exposed to the risk of dying in a given year from any of the conditions that they have or any other non-modelled cause.* As shown in Figure 2.1, the mortality risk for a given condition is dependent on the wider determinants of health, the modelled risk factors and the conditions an individual has, as well as how the conditions are managed and treated by the health care system. For example, there has been a sharp reduction in the case fatality for coronary heart disease (CHD) over the past few decades which can partly be explained by an increase in the prescription of statins that reduce an individual's likelihood of getting heart disease. For details on how we model trends in case fatality for the Cambridge Multimorbidity Score (CMS) conditions, please see the technical appendix.

All-cause mortality in our linked Clinical Practice Research Datalink (CPRD) dataset was lower than the official mortality estimates that are reported by the ONS (31). We therefore calibrated the CPRD-driven mortality in the model to the ONS estimates. We first fitted functional demographic models by sex and IMD decile to the ONS mortality rate estimates by single year of age from 2001 to 2019 (32,33) and projected all-cause mortality rates to 2040. We then inflated the case fatality rates of potentially fatal illnesses in the simulation by an age/sex/IMD decile-specific calibration factor to track the ONS mortality projections.

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* Hearing loss, irritable bowel syndrome, asthma, psychosis, anxiety and depression, constipation, pain, hypertension, chronic kidney disease and alcohol problems have very low case fatality and we assumed that mortality from these conditions is null.

7 Prevalence and its relationship with incidence and mortality

Our analysis presented in *Health in 2040: projected patterns of illness in England* uses the microsimulation model to produce future population estimates of the prevalence of ill health as defined by the CMS. Changes in the prevalence over time depend on three things: levels of onset or incidence, which refers to the flow of people into illness; mortality or remission, which removes people from the population that are living with illness; and population size and structure. Incidence rates, the share of the population that develops illness, are a key determinant of the level of illness.

It can help to think about the prevalence of illness with a bathtub analogy. The level of illness in the population is like the level of water in a bathtub. Each year there are flows into the bathtub, as people are diagnosed with conditions, and flows out of the bathtub as people recover from their illness or people with conditions die. Whether the level of water in the bathtub is higher or lower at the end of the year than at the beginning depends on the relative flows in and out. This, in turn, depends on different combinations of trends in newly diagnosed illness (incidence), remission (in the case of some conditions), mortality and population size.

Figure 7.1: A diagrammatic representation of the prevalence of long-term illness
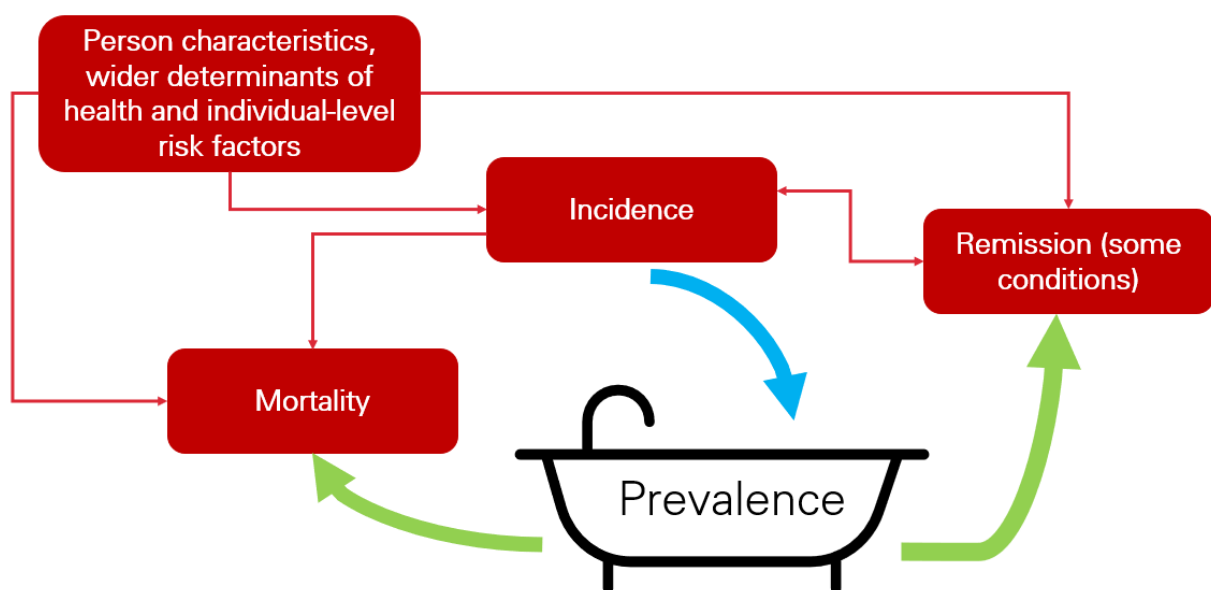
Source: Authors' representation.

Take a simple example where we consider the prevalence of an incurable condition like atrial fibrillation (AF) for a population over time. If we account for changes in age and sex then the size and structure of the population do not affect flows in and out of the bathtub; in this setting, the level of AF (bathwater) would rise if the rate of incidence (or inflow) were higher than the rate of people dying who have that condition (case

fatality).* This increase in prevalence corresponds to an expansion in morbidity. Inflows will increase if people start to develop conditions at a younger age. However, prevalence will grow even if there is no change in the age of onset if outflows (case fatality) are lower than the inflows. A reduction in case fatality rates, which brings longer life expectancies, would therefore typically increase the rate at which the level of diagnosed illness in the population is rising.

A compression of morbidity, corresponding to a reduction in overall illness or a lower level of water in the bath, occurs when rates of incidence of new illness fall below case fatality, either through high fatality rates or low incidence. This is hard to achieve because medical science is designed to keep mortality low and many of the same factors that can delay onset and thereby reduce incidence also help boost longevity. For example, a reduction in smoking delays the onset of coronary heart disease (CHD), but it also improves a person's health in other ways that increase life expectancy. Modern medicine is also increasingly successful at keeping people alive. Delay in onset does not necessarily imply a compression in morbidity as treatments allow people to then live with the condition. Therefore, although the compression and expansion of morbidity have big implications for health care resourcing, the impact on the wellbeing of the population is ambiguous. They depend on why levels of illness are changing.

So far, in this example, the size and structure of the population have been held constant. However, we know that the population is growing and is ageing. This demographic change is down to both increases in life expectancy and because large post-war birth cohorts, particularly those born in the late 1940s and the 1960s, are moving through their life cycles. The health of people at a particular age can change over time: 70-year-olds today are significantly more likely to be alive or in better health than half a century ago. These changes are captured in our age-sex-adjusted estimates. However, at any given point in time, the average 70-year-old has much higher levels of illness than the average 50-year-old. Holding rates of onset by age constant, an ageing population will have more illness. This is because population ageing implies lower mortality rates, leading to a rise in the overall number of people in ill health. The following box demonstrates the interplay of incidence, mortality and the changing population size and structure to determine the number of people with a given condition using the example of COPD.

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* For conditions such as cancer and anxiety or depression, where people go into remission, mortality and remission both act together as outflow. We use AF here for simplicity of explanation.

Box 7.1: COPD example of the relationship between incidence, mortality, prevalence and numbers of people with illness

Using the example of a single condition, we can illustrate how population changes lead to additional upward pressure for diagnosed conditions. For the sake of simplicity, we will look at the incidence, mortality and prevalence rates by age for multiple birth cohorts of men with chronic obstructive pulmonary disease (COPD), a common condition that causes breathing difficulties. In Figure B7.1 we compare the projected incidence of COPD for six cohorts of men born at the start of each decade from 1940 to 1990. The former cohort is aged between 80 and 100 years between 2020 and 2040, the latter is aged between 30 and 50 years.

Figure B7.1: Projected incidence of COPD for men by age between the years 2020 and 2040, 1940 to 1990 cohorts
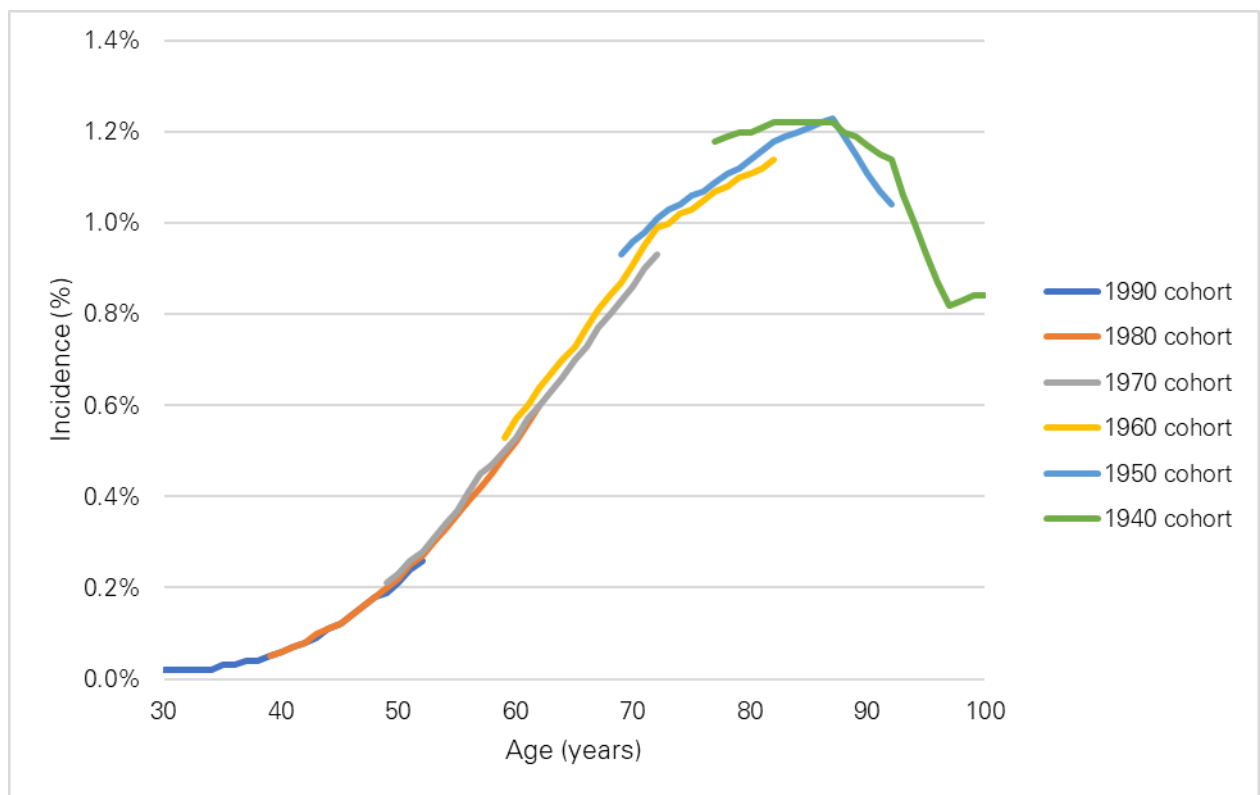
The incidence rate for COPD increases as people age but is projected to be marginally lower across birth cohorts from 1940 to 1990. After the age of 87 years, diagnosis rates for COPD begin to fall. The reduction in incidence for successive cohorts is related to the reduction in smoking prevalence in recent years, which is projected to continue in the next two decades.

These trends in incidence place downward pressure on the prevalence of COPD in the population: all else being equal, we would expect a reduction in the prevalence of COPD across cohorts. However, remembering the bathtub analogy, we need to compare the number of people entering the bath (incidence) with the number leaving (mortality rate *with* COPD). Figure B7.2 shows the mortality rates of people who have COPD.

Figure B7.2: Projected mortality rates per COPD patient for men by age between the years 2020 and 2040, 1940 to 1990 cohorts
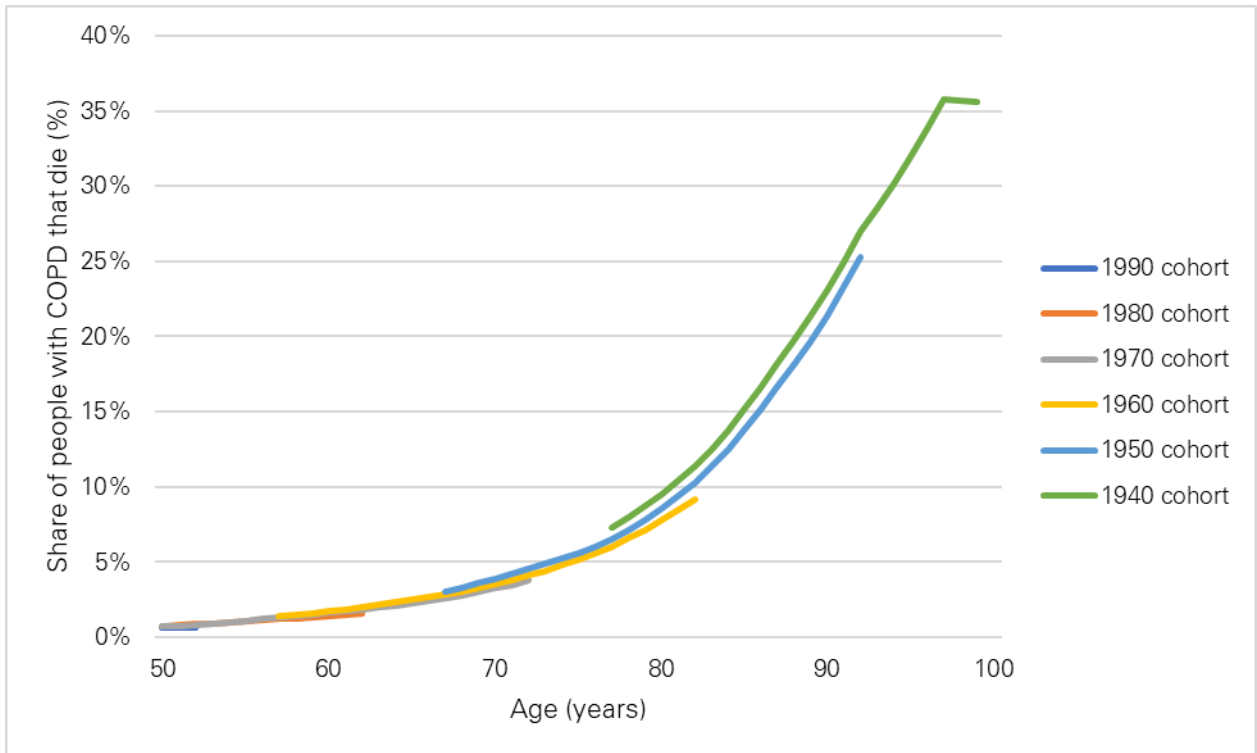
The share of people with COPD who die increases with age, but for cohorts born in different decades we see a reduction in mortality rates from birth years 1940 to 1980. This is particularly clear when comparing the 1940 cohort with the 1950 and 1960 cohorts where the green line is clearly above the blue and the yellow lines at all points.

Given that there is a downward trend in mortality and incidence rates at the same time across cohorts, we project a consistent pattern of prevalence over time in the next two decades (Figure B7.3). The combination of positive health and health care gains over time means fewer people are diagnosed with COPD, but those that are diagnosed live longer with the condition.

**Figure B7.3: Projected prevalence of COPD for men by age between the years 2020 and 2040, 1940 to 1990 cohorts**
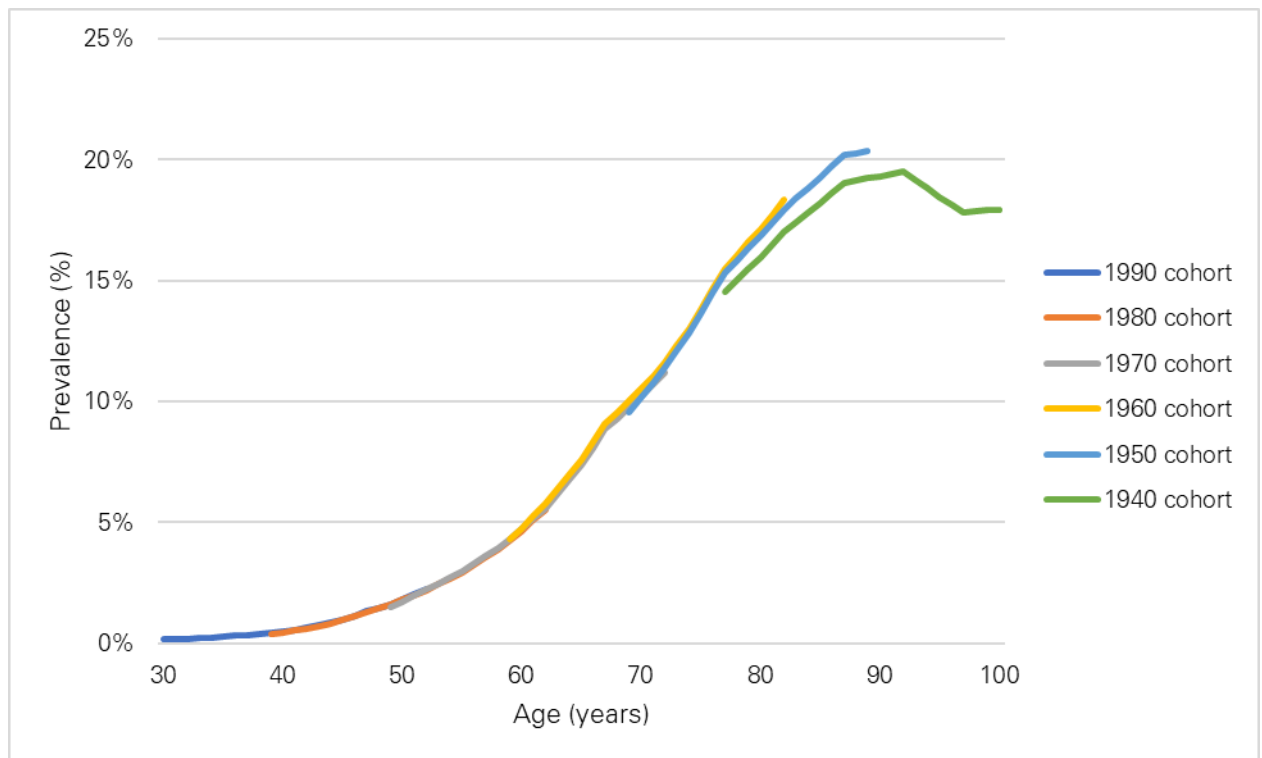
Source: Analysis of linked health care records and mortality data conducted by the REAL Centre and the University of Liverpool.

The prevalence of COPD for each cohort born between 1950 and 1990 is almost identical. People born at the start of consecutive decades are on the same prevalence paths as they age.

This unchanging prevalence across cohorts will, however, still translate into a large increase in the number of people with COPD due to the changing population structure as shown by Figure B7.4. The green line of the 1940 cohort here is below that of the blue line (1950 cohort) and yellow line (1960 cohort). This is because the number of people in the age range at which COPD is most prevalent, 70–90 years, is projected to increase by 2.8 million people between 2020 and 2040. The projected number of people aged 60 years and older in the next 20 years is therefore the strongest driver of the projected number of people living with COPD in 2040.

**Figure B7.4: Projected number of COPD cases for men by age between the years 2020 and 2040, 1940 to 1990 cohorts**

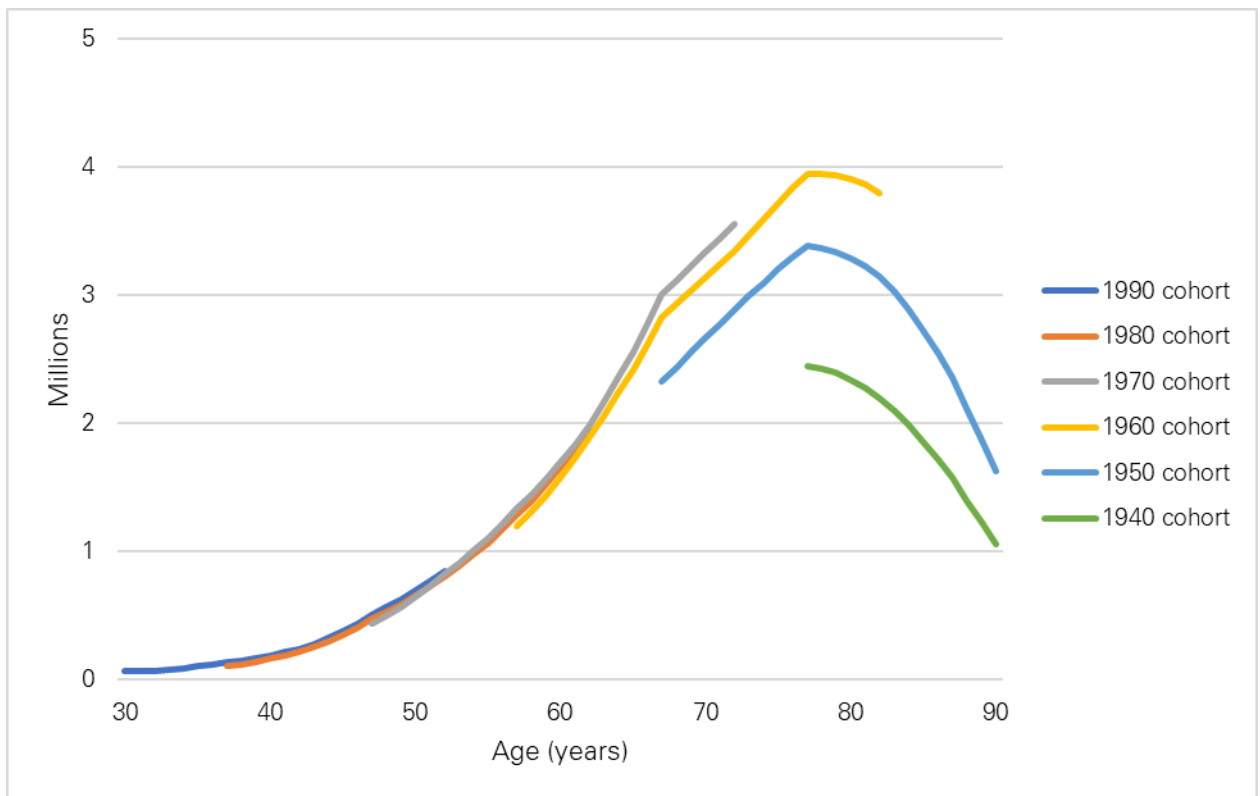**Source**: Analysis of linked health care records and mortality data conducted by the REAL Centre and the University of Liverpool.

8 Measuring ill health

Often-cited measures of population health are 'healthy' and 'disability-free' life expectancy – the number of years a person born can expect to remain in good health or without disability (34). Healthy and disability-free life expectancy are based on people's self-reported experience of illness. This is dependent on several interrelated factors such as: the presence of illness (and its effect on the ability to undertake daily activities); condition management; availability and effect of treatment, and finally the context and expectations of the person. Diagnosed illness has been shown to have a more direct relationship with health care demand. Moreover, studies have shown that the relationship between self-reported health and diagnosed health can vary for different population groups (35–38). This suggests that diagnosed illness is a more accurate predictor of demand for health care than healthy and disability-free life expectancy.

8.1 The Cambridge Multimorbidity Score

We therefore focus on levels of diagnosed illness in this report using primary care administrative data from the Clinical Practice Research Datalink (CPRD) Aurum, linked to secondary care records (from the Hospital Episode Statistics (HES)) and ONS mortality records. To quantify illness and multimorbidity more precisely, we make use of the Cambridge Multimorbidity Score (CMS) (39). The score assigns a weight or 'score' to 20 conditions based on how the illness affects patients' use of primary care, emergency health services and their likelihood of death. For instance, cancer and heart failure are given higher scores than hypertension (high blood pressure) or hearing loss because they are more likely to lead to death, unplanned hospital admissions or greater primary care needs. For those with multimorbidity, the general outcome scores are added together, meaning individuals with the same score can have a different number and combination of conditions. This provides a common metric across illnesses and allows us to aggregate multimorbidities. The assigned general outcome, primary care, unplanned admission and mortality scores for the CMS are reproduced in Table 8.1.

Table 8.1: Cambridge Multimorbidity Score conditions and their weights

Condition	Primary care consultations[1]	Unplanned admissions[2]	Mortality[2]	General outcome[3]
Dementia	1.81	156.90	124.42	**2.50**
Cancer	2.58	104.80	62.00	**1.53**
COPD	3.43	134.51	42.50	**1.46**
Atrial fibrillation	5.94	105.21	22.14	**1.34**
Heart failure	2.90	73.20	43.47	**1.18**
Constipation	3.42	72.73	35.42	**1.12**
Chronic pain	3.43	84.93	16.46	**0.92**
Epilepsy	2.13	113.42	18.26	**0.92**
Stroke/transient ischaemic attack (TIA)	1.54	90.84	20.63	**0.80**
Diabetes (type 1 or 2)	3.77	55.33	10.23	**0.75**
Alcohol problems	0.97	93.59	12.72	**0.65**
Psychosis/bipolar disorder	2.24	77.28	7.20	**0.64**
Chronic kidney disease	0.98	52.13	16.61	**0.53**
Anxiety/depression	2.12	46.61	7.04	**0.50**
Coronary heart disease	1.49	70.87	4.22	**0.49**
Connective tissue disorders	3.10	28.87	−0.39	**0.43**
Irritable bowel syndrome	1.82	8.55	−1.33	**0.21**
Asthma	1.32	22.78	−2.73	**0.19**
Hearing loss	1.04	8.93	−3.94	**0.09**
Hypertension	0.66	10.76	−2.09	**0.08**

Source: Payne et al. (39).

Note: 1. Per person-year. 2. Per 1,000 person-years. 3. Unit change associated with a change of one standard deviation in each of the three outcomes.
Negative weights can be interpreted as reflecting a negative association with the outcome of interest after controlling for other conditions.
Constipation, when diagnosed in primary care data, is likely linked to the side effects of taking opioid analgesics (strong painkillers such as codeine phosphate) and other medication. Chronic pain that leads to opioid prescribing tends to be worse and therefore constipation could be linked with higher care needs.

The use of diagnosed conditions in administrative primary care data to measure levels of illness has several advantages over using survey data. Administrative data tend to have larger and more representative patient samples and are less subjective than self-reported measures of health in surveys (37). It is however important to note that rates of diagnosis can be affected by patients' access to care and changes in diagnosis policy and practices over time. Several studies have found underdiagnosis in COPD (40), hypertension (41), type 2 diabetes (42) and dementia (43), so it is likely that the true burden of illness will be higher than what we estimate in this report.

We use the CMS rather than other multimorbidity indices such as Charlson (44) and Elixhauser (45), as it is more representative of conditions that are highly prevalent today[*] and because it outperforms the Charlson index in predicting primary care consultations and hospital admissions and, to a lesser extent, mortality (39). Of the 20 conditions in our analysis, most are considered 'permanent' because there is no cure: once someone is diagnosed with a condition, like atrial fibrillation (AF), they will forever have that condition. For six of the conditions, which are observed to be more transient in the data, we allow patients to go into remission: cancer, asthma, anxiety and depression, alcohol problems, constipation and chronic pain. For more detail on the definition of conditions please see the technical appendix (section 6).

8.2 States of illness

The Cambridge Multimorbidity Score (CMS) can be used to define tranches of ill health for an individual and for the population (39). To help summarise the data, we split the population into three groups by CMS score. These are particularly useful when projecting the total number of people with a given level of illness.

Table 8.2: Tranches of illness as defined by the Cambridge Multimorbidity Score, with percentage of population in England by age in 2019

Illness measure	CMS range	Percentage of population aged 30–69 years	Percentage of population aged 70 years and older	Percentage of total population aged 30 years and older
No illness	0	53%	12%	45%
Some illness	CMS greater than zero but up to 1.5	37%	41%	38%
Major illness	CMS greater than 1.5	10%	47%	17%

Source: Analysis of linked health care records and mortality data conducted by the REAL Centre and the University of Liverpool.

**Note**: Each column adds up to 100%.

The first group, comprising 45% of the 30 years and older population in England, have none of the 20 chronic conditions (CMS score of zero). The second group, accounting for 38% of the population, have 'some illness', defined as having a CMS of greater than zero and up to 1.5. The final group are those with 'major illness', which corresponds to having a condition or multiple conditions that individually or combined result in a CMS of greater than 1.5. 17% of the 30 years and older population fall into this group. There is no officially recognised threshold for an individual's overall CMS that indicates high health care needs or a high risk of mortality. We chose a threshold of 1.5 because it can indicate the presence of multimorbidity for conditions other than single diagnoses of cancer or dementia.

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[*] The CMS conditions comprise 65% of all disability-adjusted life years (DALY) and 60% of years lived with disability (YLD) in England in 2019 as per the Global Burden of Disease (50).

Focusing on different age groups we can see that high levels of multimorbidity are much more common in the 70 years and older population, with 47% of people living with major illness. Just 10% of the 30–69- year-old population have that level of diagnosed multimorbidity.

As illnesses tend to accumulate, many people will be diagnosed with more conditions and their CMS rises as they age. In 2019, for those aged 30 years and older in England with any illness, nearly a third of all individuals had a score greater than 1.5 (70th percentile). The mean score was 1.2 and the median score was 0.8. Figure 8.1 below shows the average level of CMS in the population in 2019, by age and the level of deprivation of their local area. Younger people have very low levels of diagnosed illness and it increases with age. By the time people reach the age of 80 years and older, the average CMS for the population across all deprivation deciles is over 2.

Figure 8.1: Average Cambridge Multimorbidity Score by age group and deprivation decile, England, 2019
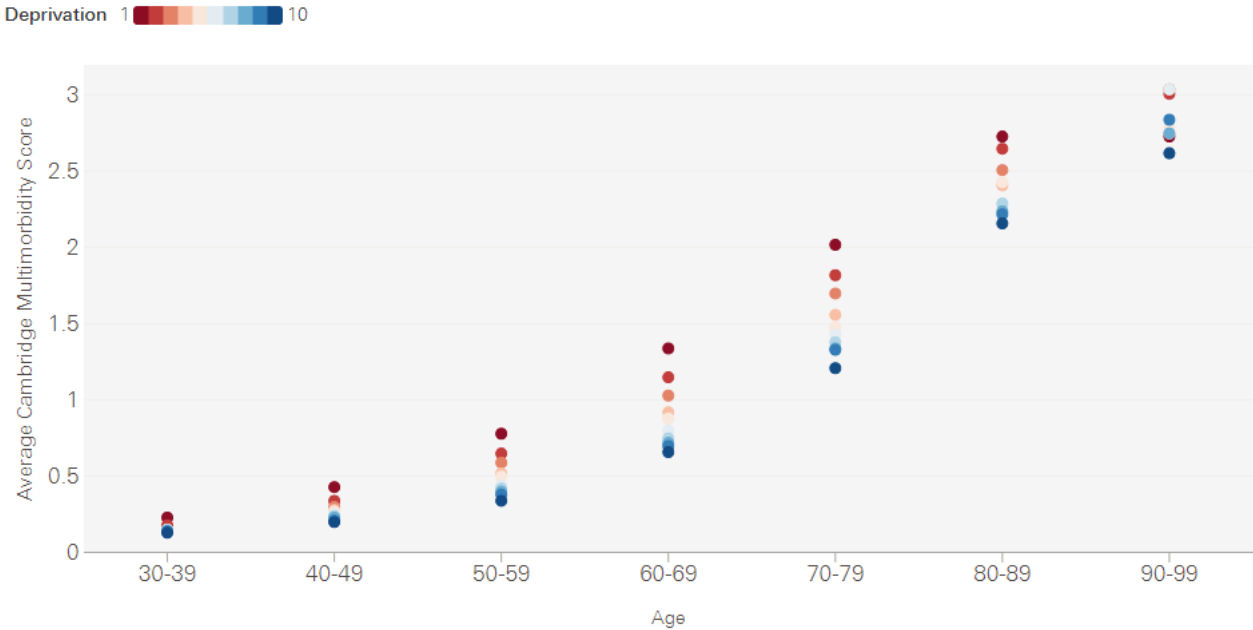
Source: Analysis of linked health care records and mortality data conducted by the REAL Centre and the University of Liverpool.

People living in deprived areas have higher levels of multimorbidity. For example, people between the ages of 60–69 years living in the most deprived areas have a CMS of close to 1.5 on average, while those in the least deprived areas have around half those levels.

8.3 Calculating life expectancy and illness-free life expectancy

The IMPACT$_{NCD}$ model is limited to the projection of illness in the population aged 30 years and older. In our report *Health in 2040: projected patterns of illness in England* and throughout this programme of research we discuss life expectancies and illness-

free life expectancies from birth. We are therefore left to make assumptions about the mortality rates and levels of illness for the population under 30 years old in our calculation of these figures. The following sections describe how we calculate these metrics as well as the assumptions involved.

8.3.1 Life expectancy

Our calculation of period life expectancies follows the methods presented in the ONS national life tables. Period life expectancies use mortality rates for different ages from a single year and assume that those mortality rates remain unchanged for the remainder of a person's life.[*] We produce life tables by 5-year age bands and sex, replicating the steps used by ONS to calculate life expectancies and health state life expectancies (46).

The first step involves mortality rates by 5-year age bands and sex. ONS uses rolling 3-year average mortality rates (eg 2017–2019) whereas in this analysis we use single-year mortality rates. As a result, we use ONS's single-year qx estimates for England to calculate the life expectancy for 2019 (qx explained below) (47). The final age band for ONS mortality rates is 90 years and older and assumes an age interval size of 9, ie the maximum possible life length is 100 years.

To calculate life expectancies, we calculate the following variables consistent with ONS's method (where x denotes the age band):

- a_x ie the fraction of the last interval of life

This is an assumption to indicate the share of the age interval that people dying within that age interval would have survived for. ONS assumes this to be half (0.5) for all age groups except age < 1 year (where it is assumed to be one-tenth due to a higher likelihood of infant mortality in the initial months of life).

- q_x ie the conditional probability that an individual that survived the start of the age interval will die during the interval

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[*] Life expectancy can be expressed in two ways – period life expectancy or cohort life expectancy. In our projections of illness, we use period life expectancy, which uses mortality rates for different ages from a single year and assumes that those mortality rates remain unchanged for the remainder of a person's life. This measure could underestimate life expectancy if, as they have done in the past, mortality rates improve over time. Cohort life expectancy, on the other hand, uses a combination of observed age-specific mortality rates for past years and projected mortality rates for future years. This measure accounts for projected future improvements in mortality for different cohorts. But due to the assumptions involved in projecting future mortality rates, there is greater uncertainty present in these estimates. It also makes it difficult to compare across time and geography due to the range of different assumptions involved. Hence, period life expectancy is used in official statistics to compare trends in mortality over time or between geographies or population subgroups.

Our life table directly begins with the q_x estimates rather than mortality rates. This is because ONS does not provide mortality rates for a single calendar year so we use ONS's single-year q_x estimates instead.

- p_x ie the conditional probability that an individual that survived the start of the age interval will survive to reach the next age band. This is $1 - q_x$
- l_x ie the number of people surviving to age band x from a hypothetical group of 100,000 births
- d_x ie number of deaths between age bands x and (x+1)
- L_x ie person-years lived in each age interval

We assume this to be 0 for the 100 years and older age category which means that everyone in our population dies when they reach 100 years of age.

- T_x ie cumulative years lived by the hypothetical group of 100,000 people from birth in the age band x and all subsequent age intervals
- e_x ie average period life expectancy at age band x

We then report the average period life expectancy at birth for our estimates.

To estimate projected life expectancies for 2040, we first use ONS's past and projected qx estimates to calculate mortality rates for 2019 and 2040. We then split the life table into two groups: those younger than 30 years old and those aged 30 years and older. For those younger than 30 years old, we use ONS's projected mortality rates for 2040. For those aged 30 years and older, we apply the projected mortality rate changes from the model for 2040 to the ONS mortality rates for 2019 to get the projected mortality rates for 2040. The model is tethered to ONS's 2020-based population projections which would be reflected in the mortality rates that we use to project life expectancy. We then follow the remaining steps as explained above to estimate the projected average period life expectancy for 2040.[*]

8.3.2 Illness-free life expectancy and major illness-free life expectancy

For illness-free life expectancy we follow the methods used by ONS in its estimation of healthy life expectancy and disability-free life expectancy (46). ONS follows the Sullivan method to calculate health state life expectancies (48). Instead of using the prevalence of people in 'good' or 'very good' health as ONS does, we use the prevalence of people with a CMS of 0 for illness-free life expectancy and the prevalence of people with a CMS up to 1.5 for major illness-free life expectancy.

We then calculate the person-years with no illness or major illness by multiplying the above prevalence with the previously estimated Lx. We then use this Lx (adjusted for illness states) to calculate estimates for Tx (adjusted for illness states) as mentioned

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[*] ONS uses calendar years for its outputs whereas we use financial years. Our estimate of projected life expectancy for 2040 is within half a year of ONS's projected life expectancy for 2040.

above. This gives us an estimate of the average number of years people are expected to spend without illness or major illness.

To estimate projected health state life expectancies for 2040, we follow the same steps as for life expectancy explained above. In addition, we use CPRD estimates of the proportion of people in different health states by age group and sex from 2019 for those aged younger than 30 years and assume no changes to these proportions until 2040. For those aged 30 years and older for 2040, we apply the median changes to the proportion of people in different health states by age group and sex from the model to the 2019 proportions of people in different health states from CPRD.

8.3.3 Numbers of people living with and without major illness

In order to present our results in the context that represents the working age population, we present the estimated and projected total numbers of people in England living with major illness from the age of 20 years onwards. We do so for 2010, 2019, 2030 and 2040 (*Health in 2040: projected patterns of illness in England*, Figures 5 and 6). In 2010 and 2019 we estimate the proportions of people living with major illness using CPRD data and the methods described above by 5-year age bands. We then assume, for people younger than 30 years, that rates of major illness stay the same from 2019 to 2040. For those aged 30 years and older, we apply the median changes to the rates of major illness by 5-year age bands to the 2019 rates of major illness. We then multiply the rates of major illness with the population by 5-year age band to get the number of people with and without major illness in each age band. Since ONS's population estimates for 2010 and 2019 have a single age band for those aged 90 years and older, we take the average rate of major illness across the age groups 90–94 years and 95–99 years to apply to the 90 years and older ONS population. For 2030 and 2040, ONS population estimates explicitly include people older than 100 years. We assume that the rate of major illness for the population aged 100 years and older is the same as that of the population aged 95–99 years.

We follow the same methods for Figures 10, 13a and 13b (*Health in 2040: projected patterns of illness in England*).

This overview of the model and its intricacies skips over mathematical details of the modelling approach. For a full description of the model, as well as a review and validation of the trends in incidence and prevalence in the analysis, together with a validation against the existing data, please refer to the technical appendix.

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