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Approaches to Projecting Future Healthcare Demand

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Abstract

Background: Existing projections of healthcare expenditure in the UK describe a wide range of possible spending futures. In part, these reflect uncertainties about growth in demand, but they also reflect differences in modelling approaches and in their underlying assumptions.

The rise in healthcare demand, and its consequent impact on expenditures, has stimulated interest among policymakers in better projecting future healthcare needs to aid the management and organisation of healthcare resources. More accurate projections are expected to allow the healthcare system to adapt and prepare for future challenges. However, with a plethora of different and emerging methodologies and approaches to project future outcomes and events, it is increasingly challenging to select appropriate techniques for a given research objective such as the demand for health care, within a specific context such as the UK National Health Service (NHS).

Objectives: This work provides a review and critique of four approaches to projection modelling: macro-level modelling, macrosimulation, microsimulation, and machine learning. Our critique assesses these different techniques in terms of appropriateness depending on the projection objective (e.g. the impact of policy changes, drivers of demand, expenditure projection), their development and implementation costs (data requirements, maintenance, development, and running times), predictive accuracy and model fit, ease of use (implementation and interpretation), transparency, and capacity for future updates when required.

Discussion: Each of the four modelling techniques has both strengths and limitations. For any given scenario, the choice among the techniques depends on the relative importance and weight placed on the particular objective, data requirements, and on the time horizon for the projection. For example, if the research objective is the long-term forecast of healthcare demand and expenditure, machine learning and macro-level models are likely to provide the most accurate models. However, if the objective is to focus on the impact of policy changes and policy scenarios, macrosimulation or microsimulation models are more suitable. The choice of time horizon of the projection, even for long-term projections, is particularly crucial, since the forecast error in the factors explaining the growth of healthcare demand and expenditure will grow as the time horizon increases.

Executive Summary

Background

Rising healthcare demand and, consequently, healthcare expenditure contribute to an increased interest among policymakers and researchers in projecting[1] future demand for health care services and associated expenditure. The expectations are that accurate projections would allow the healthcare systems to adapt and adequately prepare for future challenges. However, with the plethora of different and emerging methodologies and approaches to model future demand, it is increasingly challenging to select appropriate techniques for a given research objective.

Moreover, the definition of demand for health care is not universal and depends on the research objective. It has typically been measured using an array of proxies, in particular, healthcare expenditure (for example total and per capita healthcare expenditure), and increasingly healthcare activity or utilisation (for example hospital admissions, bed days and consultations).

The UK spent around £153 billion on the NHS in 2018/19, which represents 7.2% of the gross domestic product (GDP) and an increase in expenditure of 2% compared to the previous year (The Health Foundation 2019). Since the NHS was founded in 1948, healthcare spending has risen by an average of 3.6% a year due to, among other factors, population growth, increasing prevalence of chronic diseases, greater expectations of the use of health care, and rising costs of delivering care. The Spending Review for 2020, which predated the COVID-19 pandemic, reaffirmed the historic long-term settlement for the NHS in England by agreeing a cash increase of £33.9 billion a year by 2023-24 (HM Treasury 2020). Given this increasing trend in expected healthcare spending, projecting future demand and, consequently, costs is crucial. First, it can help ensure that the NHS is adequately resourced in line with projected demand. Second, it identifies which factors drive healthcare spending which can inform initiatives to manage demand in future. Third, it can help the NHS manage service provision to better reflect demand.

Aim

The aim of this report is to provide an overview and informed critique of models that have been used in the UK and internationally to project healthcare demand, and assess their applicability for different projection scenarios.

We provide a comparison of the projection approaches and highlight their benefits and limitations, as well as their suitability depending on research objectives and use.

Results

The modelling approaches reviewed to project future healthcare demand and healthcare costs fall into four distinct categories – macro-level models, macrosimulation, microsimulation, and machine learning algorithms. We set out and describe these models, and provide an assessment of their suitability based on appropriateness given the research objective, implementation cost, predictive accuracy and model fit, ease of use, transparency, and capacity for future updates.

Macro-level models, which encompass extrapolation and computed general equilibrium models (CGE), use aggregate data to project future demand (or growth). **Extrapolation** uses past information to predict future events. The technique is straightforward but relies on the assumption that past patterns of use remain constant over the projection window. This assumption implies that the forecast

[1] We are using the term projection rather than forecast or prediction because the former is about ‘what if’ scenarios and does not claim to say what will happen, only what might happen under a defined set of circumstances.

error in the factors explaining growth will grow as the time horizon increases, making extrapolation less appealing for long-run projections. It is also possible that behavioural changes, for example to lifestyles, will further invalidate predictions based on past behavioural relationships over the long-term. For longer-term predictions, a constrained extrapolation technique is usually preferred. This technique uses *ad hoc* constraints to limit the cost growth to prevent projected total spending rising to an infeasible share of GDP. Although the simplicity of this technique is a strength, the model cannot shed light on how the slowdown in demand will occur.

CGE modelling has a strong foundation in economic theory and provides direct answers to the question of what will happen and why. It is a flexible but complex technique capable of simulating policies/shocks, and takes into consideration the drivers of demand for, and production of, health care. However, it might not reflect reality, since it relies heavily on strong simplifying assumptions to make the theoretical models tractable.

The **macrosimulation models** project healthcare expenditure by considering the contribution of different component drivers, such as health care providers or disease categories. They allow an understanding of the relationships between different key drivers of demand, with clear assumptions and the possibility of creating and analysing alternative scenarios (e.g. different expenditure scenarios). Nevertheless, these models have limited ability to explore scenarios associated with potential policy changes, as they ignore behavioural responses of individuals to the policy under scrutiny.

Microsimulation is a method to evaluate public policies prior to their implementation. The approach models real life events by simulating the actions of the individual micro data agents (e.g. individuals or households). These models are highly complex, requiring a substantial amount of computational resources (processing power and specialised software) and data. They model many complex features of government programmes, through behavioural and dynamic microsimulation models, which can be extended to model multiple determinants of individual health (e.g. income, education) and hence demand for health care.

Machine Learning (ML) algorithms use computational methods to 'learn' information directly from data without relying on a predetermined specification of a model. While these models produce more robust predictions than, for example, extrapolation models, they require very large datasets and a large set of potential explanatory variables. These models provide limited information on the mechanisms underlying the effect of a policy change or the drivers of demand.

Each of the four modelling techniques has both strengths and limitations. The choice of approach should depend on the projection objective, data requirements, and on the time horizon for the forecast. This means that the modelling choices cannot be ranked as 'best' or 'worst', i.e. a definitive ranking is not appropriate. While machine learning and macro-level models are more attractive if the research objective is the long-term projection of healthcare demand and expenditure, macrosimulation or microsimulation models are more appealing if the objective is to analyse the impact of policy changes and policy scenarios, and to understand the underlying mechanisms of change. The time horizon of the projection is particularly crucial since forecast error in the factors explaining the growth of healthcare demand and expenditure will grow as the time horizon increases.

In conclusion, each of the modelling approaches reviewed have value depending on the specific projection objectives, and there is a clear trade-off between model simplicity and its ability to explain the drivers of future healthcare demand and expenditure.

1. Introduction

The rise of healthcare demand and, consequently, healthcare expenditure account for an increased interest among policymakers and researchers in projecting the future demand for healthcare services and associated expenditure. The expectations are that accurate projections would allow the healthcare systems to adapt and adequately prepare for future challenges. However, with the plethora of different and emerging methodologies and approaches to model future demand, it is increasingly challenging to select the most appropriate technique for a given research objective. We aim to address this problem by providing an informed critique of the existing models, and assess their applicability for different projection scenarios.

Fifty years ago, the National Health Service (NHS) in the United Kingdom (UK) consumed around 3.4 per cent of gross domestic product (GDP). In 2018/19, the UK spent around £153 billion on the NHS, representing 7.2% of GDP and an increase in expenditure of 2% compared to the previous year (The Health Foundation 2019).[2] Since the NHS was created, healthcare spending has risen by 3.6% a year due to, among other factors, population growth, increasing prevalence of chronic diseases, and rising costs of delivering care.

Existing healthcare projections for long-term healthcare expenditure in the UK show a wide range of possible spending futures. These reflect uncertainties in predicting long-term changes in drivers of demand (e.g. ageing population), but also differences in modelling approaches and the assumptions embedded within these approaches.

The most sophisticated attempt to think through and model possible future health and social care spending in the UK was carried out in 2002 by Derek Wanless (Wanless 2002). The report provided three scenario-based spending projections (up to 2022/23) for health and social care. The scenarios intended to capture particular uncertainties, based on demographic updates, changes in population health, and the likelihood of seeking care for a given level of need.

The projections from the report were reviewed to ascertain which of Wanless' three scenarios was most prevalent in 2007 (Wanless, Appleby et al. 2007). The UK was found to be somewhere between (i) a least satisfactory and most expensive scenario; and (ii) a scenario of steady and significant improvement (e.g.: health targets met, life expectancy continuing to grow rapidly). Importantly, the review recommended that forecasts be carried out at regular intervals using updated models, new information and data. Since 2002, the Office for Budget Responsibility (OBR) has produced reports on long-term projections for health care, social care, and other public spending as part of its analysis of fiscal sustainability. The OBR's latest health and long-term care projections suggest healthcare spending will rise from 7.6% of GDP in 2022/23 to 13.6% in 2067/68 (Office for Budget Responsibility 2018).

Other international institutions such as the European Commission (EC), International Monetary Fund (IMF), and Organisation for Economic Co-operation and Development (OECD) also provide projections of healthcare spending. For example, an EC study suggested that public healthcare spending would rise from around 7.5% GDP in 2007, to between 7.6% and 14.9% by 2060, depending on assumptions about population health, healthcare service productivity, and other factors (Przywara 2010).

[2] Health services in England are funded through the Department of Health and Social Care's (DHSC) budget. In 2020/21, the planned spending for the DHSC was £212 billion (in 2020/21 prices), which includes £60 billion of extra funding in response to COVID-19 pandemic The King's Fund (2021). The NHS budget and how it has changed. The NHS in a nutshell.

Factors relevant to explain the growth of healthcare spending vary according to the time horizon considered. In the short run, expenditure growth is closely linked to government budget decisions. In the medium term, technological change plays an important role in explaining growth. Risk factors, such as obesity, and changes in the prevalence of chronic diseases, become more relevant in the longer-term.

While the definition of healthcare demand is not universal, and depends on the research objective, it is typically measured using an array of proxies, in particular, as healthcare expenditure (for example total and per capita healthcare expenditure) (Wanless 2002), and increasingly as healthcare activity (for example hospital admissions, bed days and consultations (Mason, Santana et al. 2019)).

Historically, the key drivers affecting healthcare demand/expenditure include (i) demographic and health status; (ii) income; (iii) development in medical technology; (iv) health seeking behaviour; (v) health prices and productivity; and (vi) healthcare system organisation (Astolfi, Lorenzoni et al. 2012, Mason, Santana et al. 2019, Santana, Aragón et al. 2020). Appendix 5.1 provides a description of each of these drivers.

Given the scale of current spending on health and social care, and the likely pressures to spend more in future, there is a clear need for projections for long-term healthcare expenditure. The aim of this report is to provide a comprehensive overview of the main healthcare demand forecasting models that have been used in the UK and internationally. We provide a comparison of the approaches and highlight their benefits and limitations. We have not ranked the models since the choice of model is context-specific, and depends on the particular projection objectives, data requirements, and on the desired time horizon of the projection.

The next section provides a detailed description of four modelling approaches to project future healthcare demand by presenting empirical examples and addressing their strengths and limitations. Section 3 discusses these techniques and their potential applications, taking into account their strengths and limitations. Further details of the applications of the four approaches can be found in the Appendix.

2. Projection approaches

Approaches to project future healthcare demand differ in their data requirements, complexity of implementation, and ability to model policy changes. The projections further differ according to the time horizon, and are either short term (i.e. admissions to a ward in the next few days) or long term (i.e. healthcare expenditure over a 20-year period).

In this section, we review four modelling approaches to predict future healthcare demand: macro-level projection, macrosimulation, microsimulation, and machine learning. **Macro-level models** relate to modelling aggregate data, while **macro-simulation models** or cell-based models are component-based models which project healthcare expenditure at a disaggregated level, for example, by gender/age groups. **Microsimulation** is a demographic projection technique. It describes events and outcomes at the individual level with the goal of assessing short- and long-term effects of policies across years. More recently, there has been an increasing use of **machine learning** algorithms (adopted from computer science) for tackling projection challenges in health care. The technique can provide projections independently or used alongside microsimulation approaches.

While the most obvious difference among these approaches to projection models is the level of data aggregation, the most crucial difference is their ability to model various drivers of demand. For example, microsimulation models directly project future health status of the population, conditional on their background characteristics, their exposure to risk factors, and their current and past health status and chronic health conditions (see section 2.3). On the other hand, health status is implicitly modelled in cell-based models such as the Hippocrates model through the healthy-ageing hypotheses: the baseline activity rates are adjusted according to the assumed relationship between life expectancy and health status (see section 2.2). It is relatively straightforward to incorporate these factors in the predictors of a macro-simulation model (albeit at an aggregate level). However, it is challenging to include them in a machine learning model which is based on existing disaggregate data, and does not readily accommodate predicted macro changes to the system.

In this section, we describe the four modelling approaches outlined above, and provide empirical examples for each model. The choice of model depends mainly on the projection objectives, its time horizon and the data requirements. A short summary of these modelling approaches, and their strengths and limitations, is provided in Table 1.

Table 1. Summary of projection approaches

Modelling Approach	Data disaggregation	Main features	Strengths	Limitations
Macro-level, Extrapolation	Aggregate data	Projections can be based on pure extrapolation of a trend or on projected values of important explanatory variables. Appropriate for short-term projections under the assumption of clear and undisturbed trends.	Moderate data requirements; inexpensive implementation; the most direct approach to forming projections; straightforward to implement; transparent.	Not suitable for long-run projections as it does not constrain projections, e.g. to be within national income. Using a constrained extrapolation technique, growth begins to slow across the projection period. This technique cannot provide information about how the slowdown will occur.
Macro-level, Computable General Equilibrium (CGE)	Aggregate data	CGE fit data to a set of equations, which aim to capture the structure of the economy and behavioural responses of agents. CGE models capture the entire healthcare economy including demand, supply, price movements, and interactions between different sectors.	Modelling is rigorous with strong foundation in economic theory; flexible models capable of simulating a wide range of policies and shocks; they take into consideration the incentives that drive the demand for and production of health care.	Higher data requirements; projections are highly dependent on assumptions about the behaviour of health care agents; limited applicability in practice: it is very complex, may produce multiple equilibria, or even be unsolvable.
Macrosimulation	‘Cell-based’ breakdown of key characteristics	Individuals are grouped into cells according to a limited number of characteristics. Baseline healthcare activity is calculated by multiplying each cell size by its average activity in the baseline year. Baseline activity is projected forward using population projections for each cell and assumptions about changes in health status. Supply side factors can also be introduced in the models.	Moderate data requirements; inexpensive implementation and maintenance; ability to model alternative scenarios.	Limited ability to explore scenarios associated with potential policy changes.
Microsimulation	Micro-level units	These models reproduce characteristics and behaviours of populations and model the impact of changes of individual behaviour responses to policies.	Allow for detailed analysis of potential ‘what if’ scenarios, e.g. pre-implementation policies.	Higher data requirements; substantial amounts of statistical resources.
Machine learning (ML)	Micro-level units	This is a collection of different prediction algorithms. It typically uses very large datasets, separated into training data and testing data. Training datasets are used to ‘train’ the data - obtain coefficients used for predictions of the test data.	More accurate predictions compared to other models. ML algorithms routinely outperform other methods in predictions and are used in a large variety of settings.	Higher data requirements; prediction models are also considered ‘black-box’ as the user only sees the final output, that is, the relationship between variables is unobservable to the user or is difficult to interpret. Limited ability to identify and fully explain drivers of healthcare demand and expenditure.

2.1 Macro-level models

2.1.1 Extrapolation

Extrapolation is the most direct approach to project healthcare costs. It uses readily available historical aggregate data, namely country specific time-series data (e.g. healthcare expenditure per year and country) and sophisticated regression models, to analyse and project future healthcare costs. Those models usually regress a measure of healthcare costs, e.g. total annual expenditure, on its lagged (historical) values. Extrapolation also includes techniques to remove seasonality and cyclicality components from the data (National Research Council 2010).

In all extrapolation models, the underlying assumption is that the historical time series patterns remain constant over the projection window, for example that there are no structural breaks or major shifts in the series. This assumption makes long-term projections less accurate as the projection error in the factors explaining growth will grow as the time horizon increases. Projected costs may grow so quickly that total spending grows to an infeasible share of GDP. To avoid this, a constrained extrapolation technique has been used for long-term projections. This technique imposes 'shape' constraints to control the behaviour and variability of the extrapolation fit and, therefore, limit growth to a more acceptable level (Gluhovsky and Vengerov 2007). This approach has been used by several public agencies, such as the Congressional Budget Office (CBO), Office for Budget Responsibility (OBR), European Commission (EC)[3] and the International Monetary Fund (IMF).

Box 1. Empirical applications of extrapolation

Two public agencies, the Congressional Budget Office (CBO) and the Office for Budget Responsibility (OBR), use extrapolation techniques to project healthcare spending growth. In both approaches, healthcare spending growth is adjusted for demographic changes.
The CBO provide projections for Medicare, Medicaid, and other healthcare spending at an aggregate level. Their long-term projections follow 10-year baseline projections for the first decade and then it uses a constrained extrapolation approach by assuming non-healthcare consumption never declines.
The OBR publishes projections reflecting the fiscal consequences of past public sector activity and the potential fiscal impact of future public sector activity by making long-term projections of revenue, spending and financial transactions over the next 50 years.

2.1.1.1 Empirical applications

In this section, we describe how two public agencies, the CBO and the OBR, use extrapolation techniques to project healthcare spending growth. In both approaches, healthcare spending growth is adjusted for demographic changes. There are two main differences between the CBO's and OBR's assumptions for healthcare spending. First, the CBO assumes healthy ageing (that morbidity is concentrated in the final years of life) while the OBR assumes an (implicit) expansion of morbidity (that morbidity is spread across increases in lifespan). Second, the CBO considers other cost pressures in its healthcare spending projections while the OBR does not include such factors. In both approaches, projections fail to account for other important drivers of healthcare spending, such as technological change and changes in epidemiological profiles.

[3] The EC provides a detailed description of the methodology used to project healthcare spending over the next 50 years for the EU as well as for each member state European Commision (2013). Report on Public finances in EMU Brussels, Directorate-General for Economic and Financial Affairs.

1. Constrained extrapolation to project Medicare expenditures (Congressional Budget Office 2007)
The Congressional Budget Office (CBO) is a federal agency within the legislative branch of the United States (US) government that provides budget and economic information to Congress. One of its roles is to provide projections for Medicare, Medicaid, and other healthcare spending at an aggregate level. For the first 10 years, cost projections were based on the CBO's budget and economic outlook, which includes an economic forecast and projections of spending and revenues under current law[4] (known as baseline projections). The CBO projections are very detailed and produce category-specific costs (e.g. hospital inpatient care, outpatient services and physician fee schedules). Beyond 10 years, the CBO uses a constrained extrapolation approach by assuming non-healthcare consumption never declines (National Research Council 2010).[5]

The CBO considers two measures of cost growth: real per capita growth and excess cost growth. While the first captures the increase in real annual healthcare spending for an average individual, excess cost growth measures the increase in the share of the economy devoted to health care. The excess cost growth increases if the adjusted (for age, sex, and time until death) per capita healthcare spending grows faster than per capita GDP. This measure of cost growth does not closely track annual economic trends, since excess cost growth is often unusually low during periods of strong economic growth, and unusually high during periods of slow growth. Excess cost growth is therefore a more useful measure for long-term projections, while real per capita cost growth is a more reliable measure for year-to-year projections. Hence, for long-term projections, CBO uses excess cost growth instead of real per capita cost growth.

The CBO's long-term projections follow 10-year baseline projections for the first decade and then extend the baseline concept for subsequent years. Specifically, and for the year immediately following the 10-year projections, the CBO assumes excess cost growth for Medicare and Medicaid is equal to the average historical rate of growth based on the past 30 years.[6] However, if the CBO were simply to extrapolate this historical growth rate, total spending on health care would exceed total GDP. Therefore, the CBO constrains excess cost growth by slowing it down. The assumption is that households will not be willing to spend so much on health care that their real non-healthcare spending per capita would decline during the 30-year projection period (National Research Council 2010).[7]

The main advantage of this model is that it relies on a simple rule regarding patterns of household consumption: households will not be willing to reduce non-healthcare spending at any time during the projection period (National Research Council 2010). However, the CBO's approach has several limitations. First, there is a tremendous amount of uncertainty surrounding healthcare spending growth over a 30-year time horizon. Second, it is assumed that epidemiological or technological trends remain constant, as reflected by historical trends. Finally, it does not account for the consequences of increasing healthcare spending. For instance, it does not explain how healthcare labour supply will need to change to provide additional healthcare services (National Research Council 2010).

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[4] According to Public law 99-177, CBO is required to assume, in its baseline projections, that 'laws are implemented as specified and that funding for entitlement programmes is adequate to make all' National Research Council (2010). Improving health care cost projections for the medicare population: summary of a workshop, National Academies Press.
[5] Every year CBO publishes 10-year projections of the budget and also a long-term budget outlook, which provides projections for the next 30 years.
[6] The historical excess cost growth for Medicare and Medicaid is calculated by adjusting historical aggregate growth rates to remove the effects of changes in the age composition of the population, the number of beneficiaries and the per capita growth of GDP.
[7] In its latest projection of the budget 2021-2051, excess cost growth for Medicaid and Medicare is projected to move smoothly to a rate of 1 per cent by 2051.

In Table A1, we present CBO's projections of the major health care programs as a percentage of the GDP between 2017 and 2019, as well as the actual values. In 2019, the difference between the predicted and the actual values amounts to 0.4 percentage points.

2. Fiscal sustainability and public spending on health, Office for Budget Responsibility (Licchetta and Stelmach 2016)

The Office for Budget Responsibility (OBR) was established in the UK in 2010 to provide independent analysis of the UK's public finances. OBR publishes the Economic and Fiscal Outlook (EFO) yearly reports, which set out projections for the economy and the public finances over a five-year horizon.

Healthcare spending is the largest component of age-related spending in the projections. OBR classifies factors that determine healthcare spending into demographic factors such as population age structure and age-specific morbidities, and non-demographic factors such as income effects, lower productivity growth in the health sector (relative to the rest of the economy, resulting in increased relative health care costs), and technological advances.

Regarding the demographic factors, the OBR projects the size and structure of the population, based on assumptions about longevity, fertility, and net migration. It also assumes the expansion of morbidities hypothesis according to which the increase in life expectancy is associated with more years spent in ill health.

In its central projections, the OBR assumes that income elasticity is one (i.e. health care spending remains stable as a share of GDP), the health sector productivity will grow at the same rate as the rest of the economy, and ignores all other non-demographic health care spending determinants.

Licchetta and Stelmach (2016) assessed the sensitivity of their long-term healthcare spending central projections to alternative: i) assumptions about long-term productivity of the health care sector, ii) healthy ageing hypotheses (slower expansion of morbidity and compression of morbidity), iii) assumptions about income elasticity of demand, and iv) assumptions about cost pressures from other non-demographic factors (constant other pressures, declining cost pressures).

They concluded low sensitivity of the central projections to various healthy ageing hypotheses and income elasticities. However, they found that their health care projections are very sensitive to factors reflecting cost pressures beyond demographic and income effects.

In Table A2, we present OBR's central projections of public spending on health as a percentage of the national income between 2017 and 2019, as well as the actual values. In 2019, the difference between the predicted and the actual values amounts to -0.4 percentage points.

2.1.1.2 Strengths and limitations

Extrapolation is an easy to implement and transparent approach to project healthcare costs. It relies on historical aggregate data and a set of regressions that specify which factors drive the projection (National Research Council 2010). Extrapolation is a statistical approach that does not rely on economic assumptions about, for example, changes in individual behaviours and preferences against risk, market structure, and other factors that determine demand and supply.

This technique is more appropriate for short- and medium-term projections, since it relies on the assumption that past patterns remain constant over the projection window. While over the short-run, past patterns and relationships are likely to remain undisturbed, this assumption is more likely to be violated in the longer run, when population changes and technological development become key factors of cost growth, and economic dynamics are more complex. For instance, technological innovations can alter the relationships between costs and explanatory variables and make long run projections inaccurate.

In many cases, past trends for healthcare demand are reasonable approximations of future demand growth over the short run. However, even over short periods, economic conditions may change, affecting both the demand and supply for health care. For instance, austerity measures amid a worsening macroeconomic environment may affect demand through restricting access to health care, and supply through, for example, slowing down growth of the healthcare workforce. Since extrapolation does not make any assumptions about individual responses to these changes, the consequences of austerity measures would not be captured in the projections.

Another consequence of the constant relationships assumption is that projected costs may grow so quickly that total spending grows to an unfeasibly large share of GDP. The literature deals with this problem using a constrained extrapolation technique for long-term projections. This technique introduces a 'resistance point' at which healthcare cost growth (or excess cost growth) begins to gradually slow down. However, these long-run assumptions are *ad hoc*. Constrained extrapolation cannot provide information about how the slowdown will occur (e.g. through a slowdown in technological growth, via demand rationing, etc.).

2.1.2 Computed General Equilibrium (CGE) Models

Computed General Equilibrium (CGE) modelling is a sophisticated, broad modelling technique with strong foundations in economic theory. These models specify a number of equations designed to replicate the structure of the economy (e.g. government utility function subject to a budget constraint, firms' production functions, households' utility functions), relying on strong simplifying assumptions about the behaviour of economic agents. Being grounded in economic theory, results can be interpreted using an economics framework. For example, the CGE models can estimate the impact of health expenditure growth on overall economic growth, or the response of consumers or industry to changes in expenditure and prices. This technique also allows simulations on the impact of policies or shocks to the projections. For example, a CGE model could be used to assess the implications of higher levels of medical spending through capital investment in health technologies. To do so, one needs to calibrate the model, i.e. assign values to the model parameters. Aggregate macro-level data is used for this purpose, namely input-output accounts and healthcare expenditure by country.

Box 2. Empirical application of Computed General Equilibrium model

> The CGE approach was used by Borger, Rutherford et al. (2008) to project US long-term medical spending growth. New medical treatments are endogenous in the model, and the demand for medical services is conditional on the state of technology. The model projections rely on unobserved parameters, such as measures of the strength of preferences for health. These parameters were determined through different methods (e.g. calibration and time series estimations) and three scenarios were set up. Healthcare spending projections under each scenario were compared to the long run projections from the Office of the Actuary (OACT) in the Centres for Medicare and Medicaid Services (CMS).[8] Borger and colleagues project slower health spending growth: 35% under the intermediate scenario whereas CMS OACT projects 41%.

[8] CMS OACT projects a 75-year health care expenditure for the Medicare program, which are included in the annual report of the Medicare Trustees to Congress. The difference between CMS OACT and CBO projections is the methodology used. CMS OACT combines extrapolation with a CGE model whereas CBO uses more of a constrained extrapolation approach as explained in subsection 0.

2.1.2.1 Empirical applications

Borger, Rutherford et al. (2008) use CGE to project US long-term medical spending growth. In this model, new medical treatments are endogenous (i.e. determined by assumptions within the model), and the demand for medical services is conditional on the state of technology. The model predicts slower healthcare spending growth in the long run than the OACT CMS' projections (i.e. combining extrapolation with a CGE model). The authors made some simplifying assumptions (e.g. a fixed cost for innovation), which make the model less realistic.

1. Projecting long term medical spending growth (Borger, Rutherford et al. 2008)[9]

The CGE model presented by Borger, Rutherford et al. (2008) projects spending of Medicare on a 75 year time horizon based on a dynamic general equilibrium model of the US economy. CGE models typically capture the economy's supply and demand side; here by including a medical and a non-medical sector. Regarding the medical sector, the authors assume that the demand for health drives the demand for medical care, and that the latter is conditional on the state of medical knowledge. That is, as medical knowledge grows over time, new technologies are developed, and demand for medical care rises. However, whether or not healthcare expenditure rises relative to income depends on i) preferences for health relative to preferences for non-medical goods and services, and on ii) the extent to which new medical treatments (technology) are substitutes for existing care. In this sense, the adoption of new medical treatments is assumed to be endogenous to medical spending (i.e. determined by assumptions within the model), and the demand for medical services is conditional on the given level of technology.

The consumer problem is represented as a conventional three good demand system of leisure, health and non-medical goods and services. The production of goods depends on capital and labour, while the demand for goods depends on consumers' utility maximization. Health production depends on medical goods and services and medical knowledge. Health is defined as a private, non-market commodity and is introduced in the model to capture the relationship between medical innovation and the demand for medical goods and services.

The model projections rely on three unobserved parameters: reference period technology share of health output (i.e. a measure of the strength of preferences for health relative to non-medical consumption);[10] the elasticity of substitution between medical knowledge and medical care inputs in the production of health;[11] and the growth rate of medical knowledge.[12]
Using three methods (calibrating to a reference period; parameter values of estimates from the literature; and time series analyses) the authors set values for the parameters and analyse healthcare spending projections under three scenarios (low, intermediate, and high) which were compared to CMS OACT projections.

The authors recognise several limitations to their CGE model. First, the model does not have an endogenous (internal) explanation for the development of new medical technologies. Second, the degree to which innovation is cost increasing is fixed. Third, the model does not directly consider non-medical inputs to health, such as healthy behaviours.

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[9] In appendix 5.3.1 we provide a detailed description of the model.

[10] The demand for medical care is affected by improvements in health due to new medical technologies. When this parameter approaches zero, improvements in health do not affect the demand for medical care and, in this case, the model cannot provide a technology-based explanation for the growth of output share in the medical sector.

[11]If the elasticity of substitution is zero, then new technologies cannot be substituted for existing treatments, and the new technology is cost increasing.

[12] The state of medical knowledge is a non-traded public good. Although this parameter cannot be measured directly, it is determined through another parameter, the reference period technology share of health output (i.e. the strength of preferences for health).

2.1.2.2 Strengths and limitations

CGE models are flexible and capable of simulating policies and shocks. They take into consideration the drivers of demand for, and production of, health care. Also, it is possible to use CGE with heterogeneous agents, which might be of interest for policy purposes (e.g. the COVID-19 pandemic demonstrated the importance of heterogeneity, for example in age and sector of employment, in macroeconomic outcomes). However, these models heavily rely on strong simplifying assumptions from the economic theory, which may not reflect reality, they are very complex, and require substantial data.

2.2 Cell-based macrosimulation models

Cell-based macro models project healthcare expenditure or activity by different components such as provider or disease categories. The technique groups together individuals into cells according to a limited number of characteristics. Baseline healthcare activity is calculated by multiplying the number of individuals in each cell by its average activity in the baseline year. Baseline activity is projected forward using population projections for each cell and assumptions about changes in health status. Supply side factors (technology, workforce, labour costs) can also be introduced in the models. These models use administrative data at individual level (e.g. inpatient care, outpatient visits) as well as survey data (e.g. national household survey, longitudinal survey on ageing).

Cell-based modelling tends to be the dominant methodological approach to healthcare expenditure projection, accounting for a large proportion of the projection models surveyed by the OECD (Astolfi, Lorenzoni et al. 2012). Cell-based models are also applied to modelling projected demand for and expenditure on long-term care, in which context they have been extended to include projections of informal care demand (Wittenberg, Pickard et al. 1998, Comas-Herrera, Costa-i-Font et al. 2003).

Box 3. Empirical applications of cell-based macrosimulation approach

Cell-based macrosimulation was used by Wanless (2002) to project healthcare services expenditure for the UK under three scenarios. These were intended to capture particular uncertainties, based on demographic updates, changes to population health, and future choices and demands of people. The impact of technology on aggregate spending is inferred indirectly, rather than being included in the model as a specific driver.
In addition, Wren, Keegan et al. (2017) developed the 'Hippocrates model'. This model provides projections of public and private healthcare demand for Irish health and social care services, such as acute hospital, primary, community, and long-term care. This is also cell-based macrosimulation.

2.2.1 Empirical applications

We discuss two papers using cell-based macrosimulation approaches. The first projects healthcare services expenditure for the UK under three scenarios intended to capture uncertainties in changes to population demographics, health, and healthcare demand. The model does not directly assess the impact of changes in technology on aggregate health spending.

The second paper provides projections of healthcare demand for Irish private and public health and social care services. Using disaggregated data whenever possible, projections are provided for a broad range of health and social care services such as acute hospital, primary and community care. The model can inform (i) health care and social service planning in Ireland; (ii) financial planning for the healthcare system; (iii) planning for capacity, services, and staffing; and (iv) identify future demand pressures. It also provides a framework to analyse the effects of reforms and policy questions. This analysis is constrained by the availability of several datasets (e.g. there is no information on Irish healthcare expenditure by age), and the inability to link some healthcare data since there is currently no unique patient identifier in the Irish healthcare system (e.g. it is not possible to follow patients across episodes of care).

1. Securing our Future Health: Taking a Long-Term View (Wanless 2002)

Derek Wanless and the Health Trends Review team at HM Treasury (Wanless 2002) developed a model to project healthcare services expenditure, taking as baseline data NHS England spending in 2002-03. The model generates activity, unit cost, and total cost projections for each year between 2002-03 and 2022-23 and considers three scenarios.[13] These scenarios are intended to capture particular uncertainties, based on demographic updates, changes in population's health, and the future choices and demands of people. For each scenario, assumptions for two key variables are tested: (i) the extent to which the public will become more engaged in relation to their health (e.g. adopt healthy lifestyles, be aware and able to recognise symptoms of illness), and (ii) the extent of efficiency gains in the NHS.

Several factors[14] that can affect activity rates, unit costs, or total costs were incorporated into the model. These include (i) demographic changes (age and sex population projections, mortality rates); (ii) costs of the five National Service Frameworks (NSFs) for specific diseases (to meet quality standards); (iii) changes in the age-specific use of care, i.e. healthcare needs; (iv) factors impacting expenditure (e.g. waiting times and technological development); and (v) workforce modelling (developed with the Department of Health) to estimate the implications of the above changes on staffing.

The Review's modelling had three stages:

1) Projecting expenditure to reflect demographic change, but assuming healthcare needs and the quality of care remain constant.
2) Assessing changes associated with the resource implications of meeting quality standards set out in the NSFs and changes in age-specific use of care linked to changes in education, income, public expectations or public awareness.
3) Incorporating the impact of certain key drivers of healthcare expenditure that apply to all disease categories and ages (e.g. technological change, productivity gains).

Baseline data were drawn from routine administrative datasets, such as Hospital Episodes Statistics (HES). Other data, such as GP visits, were drawn from surveys. The Personal Social Services Research Unit (PSSRU) at the London School of Economics and Political Sciences provided baseline data and projections of long-term care for those aged over 65.[15]

Medical technology was assumed to contribute around 3 percentage points a year to growth in healthcare spending (although the Review acknowledged the limitation of their residual approach to measuring the impact of technology on aggregate healthcare spending, since it ignores other unobservable factors driving growth).

Projections for total health spending (per cent of GDP) under three scenarios (solid progress, slow uptake, and fully engaged) are presented in Table A3, as well as the actual values. The predicted values in all three scenarios are higher than the actual values. This difference ranges between 2.3 percentage points (fully engaged) and 3.6 percentage points (slow uptake).

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[13] In appendix 5.4.1 we provide a detailed description of each scenario.

[14] In appendix 5.4.1 we describe all the factors incorporated into the model.

[15] The PSSRU model is a cell-based macrosimulation with five main parts. The first part estimates numbers of older people with different levels of disability by age, gender, household type/informal care and housing tenure; and creates up to 1,000 population sub-groups or cells. The second part attaches a probability of receiving health and social care services and disability benefits to each cell. The third part estimates total healthcare and social services expenditure, which in the fourth part is allocated to the various sources of funding. A fifth part projects the numbers of social care staff required to deliver the projected services.

2. The Hippocrates model: Projections of demand for healthcare in Ireland, 2015-2030 (Wren, Keegan et al. 2017)[16]

The Hippocrates model, developed at the Economic and Social Research Institute (ESRI) in Dublin, provides projections of public and private healthcare demand for Irish health and social care services for the years 2015-2030. Projections are provided for a broad range of health and social care services, including acute hospital, primary, community, and long-term care.

The model is based on individual-level administrative data. Where administrative data were not available, these were supplemented by either survey data or data collected at a more aggregate level. Population projections are informed by the 2016 Census of Population and the ESRI's demographic analyses.

The first step in building the model is to estimate utilisation of health and social care services in the base year, 2015. Healthcare utilisation is measured in terms of activities such as hospital bed days, home help hours, and visits to a general practice. Activity rates for 2015 are calculated by dividing the volume of health and social care activities for each age and sex cohort in 2015 by the population volume for each age and sex cohort in that year.

The base model assumes that the baseline activity rate remains constant across all projection years. Therefore, the growth in volume of activity is a function of the baseline AR and changes in the size and structure of the population through the projection period. Three population growth scenarios (low, central, and high) were analysed based on different assumptions about mortality, migration and fertility rates.

An advanced version of the model allows the activity rate to deviate from the baseline rate based on different hypotheses about the relationship between life expectancy and health ('healthy ageing' assumptions): (i) expansion of morbidity (Gruenberg 1977), which assumes that as life expectancy increases, the years spent in ill health and disability also increase; (ii) compression of morbidity (Fries 1980), assuming healthier lifestyles will decrease or postpone the incidence of a disease until later ages; and (iii) dynamic equilibrium (Manton 1982), which assumes an increase in life expectancy is followed by an equal reduction in morbidity/disability.

Because the impact of ageing on healthcare demand varies across settings of care, 'healthy ageing' assumptions are included based on the evidence available for each setting. The 'healthy ageing' assumptions are applied by treating activity as a proxy for morbidity or disability.

In addition, a range of assumptions about future demand was made by adjusting activity rates to reflect unmet need or demand for care in the base year. The approach to estimating volumes of unmet need differ across services and is heavily influenced by the type and availability of data.

A projection based on the central population growth scenario, and the assumption that age and sex specific activity rates remain constant over the projection period, serves as the comparator scenario. Central and high population growth assumptions are combined with (sector specific) healthy ageing and unmet need assumptions to develop a preferred projection range by sector.
Table A4 to Table A6 present the projections for the three main public hospital services: total number of inpatient and day case discharges (Table A4), outpatient department attendances (Table A5), and emergency inpatient discharges (Table A6). The authors predict fewer inpatient discharges compared to the actual values, but the difference is small. As for outpatient department attendances, there were fewer attendances compared to what was predicted.

[16] In appendix 5.4.2 we provide a detailed description of the Hippocrates model.

2.2.2 Strengths and limitations

The implementation and maintenance of these models tend to be simple and relatively inexpensive. It is straightforward to model alternative expenditure scenarios and capture differences in drivers of demand by setting/sector. In addition, cell-based microsimulation models are not very demanding in terms of data requirements. Their main disadvantage is their limited ability to explore scenarios related to potential policy changes (Wren, Keegan et al. 2017). The reason is that these models ignore individual behavioural responses to the policy under scrutiny. For example, the Hippocrates model – by incorporating demand in both public and private systems – can examine the implications of a policy that transfers services from private hospitals to public hospitals, or vice versa. However, it does this by simulating changes in health expenditures, following the introduction of the policy under the assumption that individual behaviour is exogenous to the policy (e.g. individuals do not change their demand for health care).

2.3 Microsimulation Models

Microsimulation has its origins in the seminal work of Orcutt (1957), and consists of modelling real life events by simulating the actions of the individual micro units of analysis (e.g. individuals, households, etc.) that make up the system where the events occur (Brown and Harding 2004). They can be used to simulate behavioural responses to a policy change that might alter future healthcare demand (Zucchelli, Jones et al. 2012).

Zucchelli, Jones et al. (2012), in their review of microsimulation models, explain that they consist of two main components: a micro-dataset and a model that informs behavioural change under a current and a counterfactual policy scenario. The models can be classified as arithmetical or behavioural – i.e. whether the model ignores or accounts for the behavioural response of agents to a policy reform – and as static or dynamic – i.e. whether the model incorporates a time element in the analysis or not. These models are highly complex, as they model many complex features of government programmes. Behavioural and dynamic microsimulation models could be extended, in principle, to model many determinants of individual health (e.g. income changes, lifestyles) and thence demand for health care.

This microsimulation technique uses individual records taken from administrative data or survey data as their primary data source. To fill information gaps, data are augmented with information imported from other sources using imputation or matching techniques. The baseline dataset, which can comprise several sources, should be representative of the population relevant for the policy being simulated. It is common to collect data on an annual basis. For example, the primary dataset might be individual-level data on healthcare costs and utilisation. These data might be combined with data on some specific diseases (e.g. diabetes, cancer) and risk factors.

Box 4. Empirical applications of microsimulation approach

The two most comprehensive dynamic microsimulation models with a health module are the RAND Future Elderly Model (FEM) and the Population Health Model (POHEM).
The FEM is an economic-demographic model developed to examine health and healthcare costs among the elderly Medicare population in the US. Using a representative sample, the model begins with health status in the current year and estimates the medical services needed and simulates the consequent change in health outcomes.
POHEM was developed to project healthcare costs and health outcomes, such as life expectancy and quality of life, of the Canadian population using individual disease states, risk factors and health determinants.
Both models allow the impact of programme interventions or a policy to be assessed.

2.3.1 Empirical applications

In this section, we examine two dynamic microsimulation models that contains health modules: RAND Future Elderly Model (FEM) and Population Health Model (POHEM).

The FEM and POHEM are the two main examples of dynamic microsimulation models related to health and healthcare spending. The FEM is an economic-demographic model developed to examine health and healthcare costs among the elderly (65+) Medicare population in the US. Using all elderly individuals from a nationally representative survey of the Medicare population, the model begins with the health status in the current year and estimates the medical services needed to meet healthcare needs. Then it simulates the likely health status in the following year due to receipt of medical care, ageing and changes in morbidity and simulates the change in health outcomes. The model is then rolled forwards, which implies incorporating the health of younger individuals who become eligible for Medicare. The model is used to explore policy questions such as how Medicare costs might be affected by trends in health status. FEM can simulate potential health developments together with government health expenditure.

POHEM was developed to project healthcare costs and health outcomes (life expectancy, quality of life) of the Canadian population using individual disease states, risk factors, and health determinants. POHEM is one of the few models that simultaneously account for the progression and interactions of multiple health conditions. In a similar manner to FEM, POHEM allows the impact of programme interventions or policies to be assessed.

In appendix 5.5, we examine three additional dynamic microsimulation models: (i) the APPSIM model projecting healthcare expenditure under different demographic and policy scenarios (appendix 5.5.3); (ii) the NCDMod model simulating multiple chronic diseases and associated risk factors (appendix 5.5.4); and (iii) a model projecting outpatient healthcare expenditure (appendix 5.5.5). We also describe two dynamic microsimulation models applied to the UK: the SAGE model (appendix 5.5.6) and the Population Ageing and Care Simulation (PACSim) model (appendix **Error! Reference source n ot found.**). These models all have the same framework as FEM and POHEM, and hence are not described in detail here.

1. RAND Future Elderly Model (FEM) (Goldman, Shekelle et al. 2004)

The Future Elderly Model (FEM) is a microsimulation model, developed by RAND in the early 2000s, to understand how medical breakthroughs and demographic trends are likely to affect future US Medicare costs. FEM tracks older (age 65 and above), Medicare-eligible individuals over time to project their health conditions, their functional status, and ultimately their Medicare and total healthcare expenditures. The model is able to predict the costs to Medicare for treating the elderly, given current health status and disability trends continue, and to simulate and evaluate a variety of scenarios regarding the future healthcare environment.

FEM involves three phases, i.e., three combined models:[17]

1. ***Individual trajectories*** *for a number of health conditions (e.g. cancer, heart diseases and stroke) and disability status.* This phase provides the basefile for model users to 'generate' cohorts by health condition such that as the simulation proceeds outcomes can be measured for the population aged 65 and older in any given year in any given cohort.
2. ***The rejuvenation sample*** *ensures that the data remains representative of the population aged 65 years or over.* This is done annually with a newly entering cohort of 65-year-olds and individuals exiting the model due to death.
3. ***Projections*** *of future Medicare and total healthcare expenditures based on the demographic and health characteristics of the population.*

These models were integrated by first estimating costs for the representative cohort. Then individuals were 'aged' one year using the health status model. Individuals were assigned to a health condition using proportional hazard modelling. Then the population was updated by introducing the new 65-year-olds and removing those who died, and healthcare costs on the simulated cohort can then be estimated again. This process is repeated for each year until a terminal date of interest is reached.

FEM is a complex model that requires good data and several assumptions regarding the health transitions. In this model, health states were treated as 'absorbing'; that is, it is assumed that chronic conditions, once acquired, remain for life.

The advantage of the FEM framework is that it permits counterfactual analyses of health policy interventions or changes to future trends. Besides the cost projections, the health transitions model, which computes the probabilities of transiting across various health states, is itself important to predict specific future healthcare demand, and demand for community and social care.

FEM also allows more heterogeneity, compared to a cell-based approach, since it models real cohorts (followed at the individual level) rather than synthetic cohorts.

2. Population Health Model (POHEM) **(Hennessy, Flanagan et al. 2015)**
The Population Health Model (POHEM), a microsimulation model developed by Statistics Canada in the early 1990s, was conceptualised and built to assess the impact of policy programmes and interventions by simulating lifecycle dynamics, health status, and health outcomes of the Canadian population.

POHEM involves six steps:

1. Model specification: Identifies model structure, health determinants, risk factors, and data sources as well as policy-relevant and feasible counterfactual scenarios.
2. The population can be defined in two different ways[18]:
    a. The initial population is defined using a cross-sectional survey representative of the Canadian household population aged 12 and over. This provides a set of individual characteristics (socio-demographic variables, health risk variables, and health status variables) that are updated and transitioned in step 3.
    b. The synthetic population is created through the simulation of individual life trajectories using individual-level data. It is not taken from a survey and instead can be constructed to have any desired set of demographic, health state properties one

[17] In appendix 5.5.1 we provide a more detailed explanation of these three phases.
[18] In appendix 5.5.2 we discuss the main advantages and limitations of both approaches.

might want to study. The information drawn from these data take the form of transition patterns between health and socioeconomic states. These simulations generate 'individual synthetic biographies, starting at birth and moving through life event by event until death' (Hennessy, Flanagan et al. 2015).

3. Dynamic updates and risk transitions: Individual disease states, risk factors, and health determinants are transitioned using empirically-derived predictive algorithms and risk transition models.
4. Validation and calibration:
    a. Internally: Computer and code parameters are checked against the output.
    b. Externally (when possible): Estimates are compared against other sources of data not used to build the model. If a large mismatch is found, a calibration process (defined *a priori*) is pursued.
5. Projection: Once estimates are validated, projections of health states and risk factors are produced. Projections reflect a baseline trend in health states or risk factors and other baseline societal factors that affect disease risk.
6. Counterfactual analysis: projections of counterfactual scenarios are produced to assess the impact of interventions on population health outcomes.

Similar to FEM, POHEM has intensive data requirements, and it also allows policymakers to forecast the likely effects of a policy change. POHEM has been applied to several diseases, such as cardiovascular disease (Manuel, Tuna et al. 2014), cancer (Will, Berthelot et al. 2001), and osteoarthritis (Kopec, Sayre et al. 2010).

2.3.2 Strengths and limitations

Microsimulation is a method to evaluate public policies prior to their implementation. This method can account for population heterogeneity with a focus on individuals. In a dynamic model, it is possible to assess short- and long-term effects of policies, as they are capable of measuring the effects of a policy across years.

The microsimulation approach, however, has some limitations. First, and inherent in all mathematical modelling, is the oversimplification of real-life scenarios. These models rely on a set of assumptions about the behaviour of individuals. Therefore, for the microsimulation exercise to be valid, it is important to use credible assumptions. Second, these models require a large amount of data from a variety of sources. Sometimes data are not available and, when they are, the process of combining different sources together can be intensive. Finally, and given the complexity of microsimulation models, summarising and describing the results can be challenging. This is crucial when delivering key messages to policy makers.

2.4 Machine learning techniques

The aim of projection modelling is to accurately predict (future) outcomes to inform policy. For these types of models, minimising prediction error is a relevant objective and this is the focus of machine learning techniques (Kleinberg, Ludwig et al. 2015).

Machine learning (ML) generally refers to a (computer science) field that *develops algorithms to be used for prediction, classification, and clustering or grouping*[19] *tasks with data* (Athey and Imbens 2019). It is extensively used across various fields, including image and data processing; however, its adoption in economics was relatively slow (Bajari, Nekipelov et al. 2015). This is due to several factors,

[19] In ML, classification typically refers to cases in which observations are assigned pre-defined labels. On the contrary, clustering (or grouping) deals with cases where similar observations are grouped together, based on their similarity (using their features) but without any prior pre-defined labels.

including reliance of ML on very large datasets. Depending on the ML specific algorithm used, we might require several million observations for the analysis. While ML can generally be used on different data types, including individual level/micro data and survey data, often the requirement on the size of the dataset naturally limits the data type to the micro level. Another important factor is the 'black-box' nature of the algorithms, by which we do not observe the contribution of individual variables on the final outcome. The latter is particularly problematic in economics where policy inference is often the target of analysis. Understanding the underpinning mechanisms is an important step for many policy recommendations. This is often missing in algorithms that focus on a single objective of maximising predictive accuracy. However, due to recent developments in the ML field and increased attention to the superior prediction power of ML algorithms compared to standard econometric models, the method is gaining greater popularity (Athey and Imbens 2019).

2.4.1 Popular machine learning algorithms

Bajari, Nekipelov et al. (2015) provide an overview of ML methods for demand estimation, with a particular emphasis on their role in prediction. While there are many other algorithms for ML available (with new approaches constantly in development), these provide a solid toolkit to use for most health policy prediction problems. They can be classified and described as follows:

- **Decision** Trees (DT) are non-parametric methods used for classification (outcome is a discrete variable) and regression (outcome is a continuous variable). They work by partitioning the decision space into series of (tree-like) decision nodes. Algorithms for constructing decision trees usually work top-down, by choosing a variable at each step that best splits the set of items (Rokach and Maimon 2005), with the definition of 'best' varying across algorithms. For example, a node might represent a particular patient characteristic (i.e. presence of a particular health comorbidity), or details of the care received (i.e. had a particular procedure or not). The nodes lead us to a particular class, which is the outcome that we want to predict. Compared to most ML models, decision trees are relatively easy to understand and interpret as they can be visualised. While this enables us to observe the role of individual predictors in the decisions, in practice, decision trees are often very complex. The HRG grouping system used in the NHS was designed with the help of decision trees (NHS Information Centre for Health and Social Care 2007).
- **Random forests** expand on the idea of decision trees and introduces randomness into the set of explanatory variables considered for splitting at node level. Before each split, only a (random[20]) subset of variables is included in the split search. Repeating this across many (thousands of) trees results in a forest of random trees. To reach a decision using a random forest we simply take the majority vote of all the trees (when we have classification problem) or the mean/median across all trees (when undertaking a regression task)[21]. Random forests generally outperform decision trees in their predictive power (Bajari, Nekipelov et al. 2015); however, unlike in decision trees, random forests are very much a 'black-box', as the role of individual variables in the prediction varies across trees and is unobserved.
- **LASSO** (Least absolute shrinkage and selection operator) is a shrinkage and variable selection method for linear regression models, where predictions of a dependent variable are of key focus. The goal of LASSO regression is to select a subset of covariates (and interactions between

[20] This means each tree gets the full set of variables (typically referred as features in ML literature), but at each node, only a random subset of variables is considered. The idea behind this is to stochastically construct many different predictors and then aggregate them into a single predictor. Without the additional randomness the individual predictors would likely be correlated.

[21] For example, if 1/3 of trees predicts A and 2/3 of trees predict B, then the final prediction of the random forest is B. Similarly, if we predict a continuous number, for example age, the final prediction will be the mean predicted age across all trees.

covariates) to minimise prediction error. This is done by imposing a constraint on the model parameters that causes regression coefficients for some variables to shrink toward zero (Tibshirani 1996). Variables with a regression coefficient equal to zero after the shrinkage are then excluded from the model; variables with non-zero regression coefficients are those that are most strongly associated with the dependant variable. Explanatory variables can be continuous or categorical.

- **Neural Networks** While not included in the Bajari, Nekipelov et al. (2015) list of algorithms, neural networks are some of the most powerful ML algorithms. They are used in complex applications, including image and voice recognition. The algorithms are inspired by the workings of the human brain; the algorithm is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in the human brain. Figure 1 below shows an example of a simple neuron network. Unlike in linear regression, where we estimate the outcome (dependent variable) directly from the input variables (explanatory variables), in this case we have a so-called hidden layer. Initially all the weights (w_1, w_2, w_3,…; analogous to coefficients in a linear regression) are assigned randomly and then refined through backwards and forwards propagation (this constitutes the *learning* part). After thousands of repetitions the weights are set in a way to best predict the outcome.

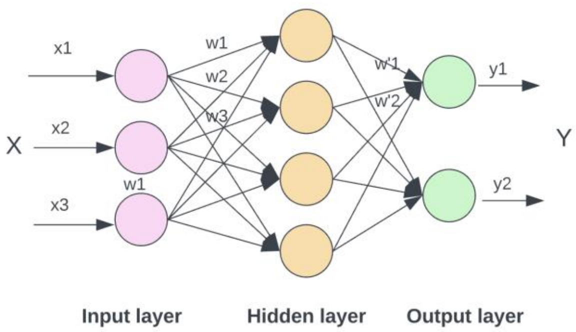

Figure 1. Example of a simple neural network

The output from the ML programmes depends on the algorithm used. In most cases, the result is a complex algorithm that can be applied to any data for which we want to predict outcomes.

Box 5. Empirical applications of machine learning methods

ML methods are gaining popularity in healthcare research. ML has been used to predict mortality of COVID-19 patients (Knight, Ho et al. 2020), next-day regional ambulance demand (Lin, Ho et al. 2020), and demand for specific health conditions such as for cardiovascular admission (Qiu, Luo et al. 2020). ML is increasingly used in the NHS to predict demand. In 2020, the NHS started a trial of a ML system designed to help hospitals predict the upcoming demand for intensive care beds and ventilators needed to treat patients with COVID-19 (NHS Digital 2020). Another project from a team at Surrey and Borders Partnership NHS Foundation Trust will use ML to develop a digital dashboard to predict length of stay of inpatients at the trust and patient flow.[22]

[22] More information about this project can be found here.

2.4.2 Empirical applications

While ML methods are gaining popularity, most of the existing examples of applications in the healthcare setting are within the computer science literature rather than the economics/policy literature. In the majority of these cases, the objective is typically a comparison of available algorithms and their suitability accounting for data limitations, rather than for answering a policy question per se.

Recently, ML has been used to predict mortality of COVID patients based on their clinical data upon admission. Using gradient boosting decision trees and data from 260 hospitals across England, Scotland, and Wales, the authors created an easy-to-use risk stratification score. The model outperformed existing scores and can be used to stratify patients admitted to hospital with COVID-19 into different management groups (Knight, Ho et al. 2020).

Lin, Ho et al. (2020) used ML to predict next-day regional ambulance demand using data from Singapore. Similarly, Chen and Lu (2014) projected demand for ambulances using the Geographic Information System (GIS) for New Taipei City. They applied a variety of ML models, with the best prediction model resulting in approximately 23% error rate.[23]

As in most ML projects, all of the above research focuses on minimising the prediction error, rather than answering a direct policy questions, e.g. exploring drivers of demand for ambulatory services.

ML is increasingly used in the NHS to predict demand. In April 2020, the NHS started a trial of a ML system designed to help hospitals predict the upcoming demand for intensive care beds and ventilators needed to treat patients with COVID-19. Resulting predictions are made at hospital and regional levels, rather than at the patient level. The system was designed in a collaboration between NHS Digital, Public Health England, and the University of Cambridge (NHS Digital 2020). Further examples of ML used in the NHS include a project run by Surrey and Borders Partnership NHS Foundation Trust (in partnership with The Health Foundation), in which they aim to project length of stay of inpatients at the trust and predict patient flows (The Health Foundation).

2.4.3 Strengths and limitations

There are many advantages of ML, compared to other techniques, when used for predicting outcomes. For example, its prediction power usually surpasses that of alternative techniques (Athey and Imbens 2019).

However, it is also associated with several limitations. ML algorithms usually require large volumes of data and a large set of potential explanatory (input) variables to form accurate predictions. Hence, it is of limited use in cases with restricted numbers of data points. Furthermore, because it is so heavily reliant on the particular data to hand, algorithms are not necessarily transferable across datasets (e.g. if the coding differs across, say, two countries the algorithm will not work). Most of the algorithms consist of what are often termed a 'black-box', where the relationship between variables is unobservable to the user.[24] This is often considered to be the reason for ML's slow adoption rate in economics, as economists are usually interested in explaining the effect, rather than solely predicting it. The techniques are, however, likely to be of value for projecting outcomes, particularly where projections, rather than the way its inputs are used, is the main goal of the modelling exercise.

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[23] In appendix 5.6 we provide more examples of studies using ML algorithms to answer specific questions about healthcare demand (e.g. demand for cardiovascular admissions).

[24] Similarly to the econometric models, the user still specifies which variables are used in the ML algorithm, but cannot deduce the relationship between variables.

3. Discussion

This report reviews four modelling approaches that could be adopted to project future demand for healthcare and the associated costs – macro-level models, macrosimulation, microsimulation, and machine learning algorithm. The approaches differ in their appropriateness depending on the specific projection objective, their implementation costs, model predictive accuracy and fit, their ease of use and transparency, and their capacity for implementing future updates.

The macro-level models, extrapolation and Computed General Equilibrium (CGE), use aggregate data to project future demand (or growth). **Extrapolation** uses past information to predict future events. Despite being a simple and straightforward technique, it relies on the assumption that past patterns remain constant over the projection window. This assumption makes extrapolation inappropriate to use for long-run projections, as the projection error in the factors explaining growth will grow as the time horizon increases. However, it is possible to use a constrained extrapolation technique for long-term projections. This technique imposes restrictions on the model to limit cost growth to prevent projected total spending rising to an infeasible share of GDP. Despite the simplicity of this technique, the assumptions for limiting growth are *ad hoc,* and the model cannot shed light on how the slowdown in demand will occur. In addition, both approaches are unable to determine the mechanism that drives the demand for health care.

CGE has a strong foundation in economic theory and provides a direct answer to the question of what will happen and why. It is a flexible technique capable of simulating policies/shocks, and it takes into consideration the drivers of demand for, and production of, health care. However, this technique is heavily reliant on strong simplifying assumptions, which may not reflect reality. The complexity of this technique means that its application to healthcare contexts is limited.

The **macrosimulation models** project healthcare expenditure by different components, such as provider or disease categories. They allow an understanding of the relationships between different key drivers of demand, with clear assumptions and the possibility of creating and analysing alternative scenarios (e.g. different expenditure scenarios). Nevertheless, these models have limited ability to explore scenarios associated with potential policy changes.

Microsimulation is a method to evaluate public policies prior to their implementation. It models real life events by simulating the actions of the individual using micro data analysis. It focuses on the individual pathway between health states and healthcare utilisation. While this technique has the ability to explore which factors/drivers contribute to an increasing healthcare demand and expenditure for long-term healthcare, it requires a substantial amount of statistical resources and data.

Machine Learning algorithms use computational methods to 'learn' information directly from data without relying on a predetermined specification of a model. These models do not focus on causality, which makes them unsuitable if interest lies in identifying the causal effects of a policy or the drivers/factors of demand. While machine learning models can produce more robust predictions than, for example, extrapolation models, they require very large datasets and a large set of potential explanatory variables.

Each of the four modelling techniques has both strengths and limitations. The choice should rely on the specific projection objectives, data requirements, and on the time horizon for the projection, so a definitive ranking of the models is neither meaningful nor helpful. Extrapolation models are only suitable for short to medium run projections. In the long run, these models can lead to unrealistic estimates of healthcare costs as a share of GDP. Constrained extrapolation models impose some restrictions on the system to limit cost growth, but they do not take into account future structural changes to demand drivers and, therefore, are not ideal for long-term projections. Because extrapolation is the most direct and easy to implement approach, it may be the preferred option for short-term predictions. If the research objective is to model long-term healthcare expenditure as a function of various drivers of demand, macrosimulation is likely to be the best option, as it combines relatively easy implementation and moderate data requirements with the ability to model drivers of demand and explore alternative scenarios. If the decision maker is not interested in modelling the drivers of demand, but their focus is on making the most accurate predictions of healthcare expenditure, then machine learning is likely to outperform other methods and be the preferred option assuming sufficient availability of data. Figure 2 summarises this discussion.

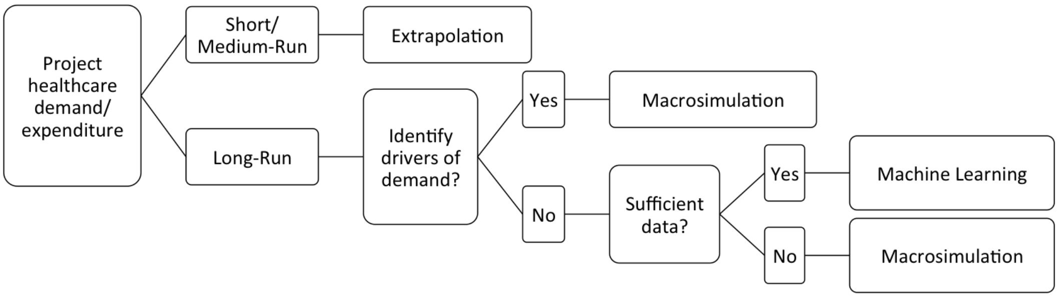

Figure 2. Decision Tree: Project healthcare demand/expenditure

If the objective is to analyse the impact of policy changes, microsimulation models are the most appropriate as they can simulate behavioural responses to a policy change that may alter future healthcare demand. Microsimulation models can also be used to project healthcare expenditure under various scenarios (e.g. scenarios about the population growth), but macrosimulation models might be preferred as they have moderate data requirements and are inexpensive to implement and maintain. In Figure 3 we summarise these decisions.

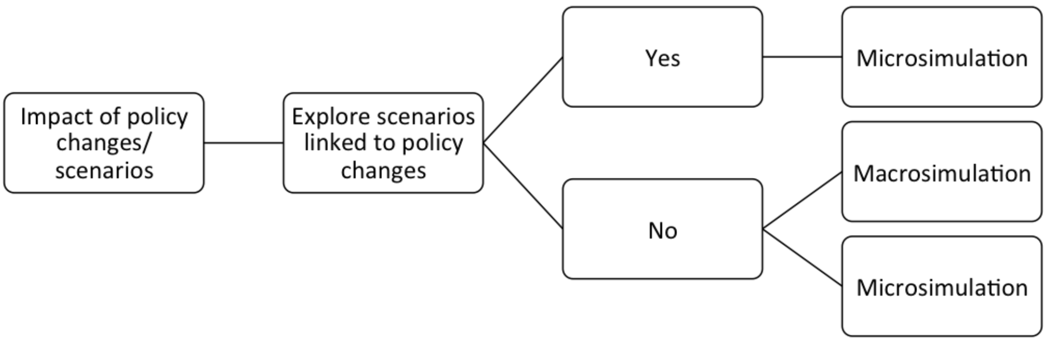

Figure 3. Decision Tree: Impact of policy changes/scenarios

The CGE models are not included in figures 2 and 3 because their complexity and limited applicability to healthcare offset their advantages when alternative models exist.

Note that the time horizon of the projection is particularly crucial, since projection error in the factors explaining the growth of healthcare demand and expenditure will grow as the time horizon increases.

To account for an external shock, such as COVID-19, the choice of model would depend on approaches that are more flexible and where projections can adapt more quickly to real-time events. The models that potentially offer such flexibility for projecting expenditure in the presence of an exogenous shock such as COVID-19 are macrosimulation and microsimulation. However, it should be recognised that behavioural and economic impacts of a pandemic such as COVID-19 are substantial and diverse, and it would be a huge and complex task to embed these effectively within a simulation-based model, particularly at the individual level.

As an example, Keegan, Brick et al. (2020) use an approach based on the Hippocrates Model to provide the baseline estimates of expenditure in 2018 for public acute hospitals and psychiatric inpatient services in Ireland, and to predict expenditure for these services to 2035. The new projections take account of the impact of COVID-19 on population (adjusting mortality, net international migration, and population estimates for 2020 downwards), unmet demand (captured by waiting times and updated taking into account figures from October 2020), and economic growth (updated using the macroeconomic model COSMO, a structural macroeconometric model of the Irish economy[25]).

In conclusion, it is not useful to explicitly rank the models or identify which is 'best', since the choice of model depends on the specific projection objectives, data requirements, and on the time horizon of interest.

[25] For a full description of the mechanisms and behaviour of the model please check Bergin, A., et al. (2017). COSMO: A new COre Structural MOdel for Ireland. Dublin, Economic and Social Research Institute. Garcia Rodriguez, A., et al. (2021). Exploring the impact of COVID-19 and recovery paths for the economy. Dublin, ESRI Working Paper, No. 706.

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5. Appendix

In this section, we provide a detailed description of the drivers of demand/expenditure (subsection 5.1) and of the applications of the four approaches (subsections 5.2 to 5.6).

5.1 Drivers of demand/expenditure

In this section, we provide a description of the key drivers of demand/expenditure (Astolfi, Lorenzoni et al. 2012, Mason, Santana et al. 2019, Santana, Aragón et al. 2020), with an extended discussion on the research of each driver: (i) demographic and health status; (ii) income; (iii) development in medical technology; (iv) health seeking behaviour; (v) healthcare prices and productivity; and (vi) healthcare system organisation.

i. Demographic factors and health status

Demographic factors are often considered as one of the most important drivers of healthcare demand. For instance, early research identified population ageing as the main determinant of rising healthcare spending (Heller, Hemming et al. 1986). However, this popular notion is over-simplistic. In fact, the effect of population ageing on healthcare demand growth is more complex, and is a function of three other factors: remaining lifetime (or time to death (TTD)), health status (comprising morbidities and disability), and life expectancy.

In a seminal study, Zweifel, Felder et al. (1999), using Swiss data, found that the impact of age on healthcare demand diminishes once TTD is taken into account, i.e. age is a 'red herring' that acts as a proxy for TTD. The rationale behind the 'red herring' hypothesis is that the positive relationship between age and healthcare expenditure is observed because, as individuals age, they get closer to death and, during the terminal years, they receive more aggressive and expensive treatments. Therefore, closeness to death is more important than age in projecting healthcare costs. The 'red herring' hypothesis triggered a long-standing debate about the influence of population ageing on the growth of healthcare demand. The hypothesis was supported by a large number of empirical studies (Seshamani and Gray 2004, Seshamani and Gray 2004, Zweifel, Felder et al. 2004, Felder, Werblow et al. 2010, Wong, van Baal et al. 2011, Geue, Briggs et al. 2014, Hazra, Rudisill et al. 2018). Other authors challenged Zweifel, Felder et al. (1999) on methodological grounds (Salas and Raftery 2001 , Dow and Norton 2002) or provided evidence against the 'red herring' hypothesis (Westerhout 2006, Breyer and Felder 2006).

The relative importance of age and TTD in determining healthcare demand is closely related to health status. If the most serious morbidities and disability are experienced closer to death, ageing seems to be less relevant. On the other hand, age maybe a stronger predictor of healthcare demand over a prolonged period of living with morbidities and disability. This may explain why the literature has, in general, found a more significant role of ageing for patients using long-term care (Werblow, Felder et al. 2007, Colombier and Weber 2011, Karlsson and Klohn 2011).

The effect of population ageing on healthcare demand is further complicated by the relationship between life expectancy and morbidities. This dynamic relationship is captured by the 'healthy ageing' hypotheses. The compression of morbidity hypothesis (Fries 1980) states that increases in life expectancy, resulting from medical progress and improvements in lifestyle and socioeconomic conditions, are accompanied by larger increases in the number of years lived in good or mild ill health. Therefore, the onset of chronic diseases and disability are compressed into an ever-decreasing proportion of an individual's life. The expansion of morbidity hypothesis (Olshansky, Rudberg et al. 1991), on the other hand, states that medical progress has limited impact on the incidence of disease, but successfully improves the survival probabilities for a number of chronic diseases requiring life-long treatment. Therefore, if life expectancy increases, the years spent in ill health or disability also increase. Between the compression and expansion of morbidity lies the dynamic equilibrium hypothesis (Manton 1982) stating that, as life expectancy increases, the absolute number of years lived in good or mild ill health increases by an amount equivalent to the increased life expectancy.

Therefore, the impact of changes in the age structure of the population on healthcare demand growth depends on the complex dynamics between age, TTD, morbidities and disability, and life expectancy.

ii. Income

National income is a strong predictor of cross-country differences in healthcare spending. However, the empirical literature has provided mixed evidence on the magnitude of the income elasticity of demand, with some studies reporting income elasticities significantly greater than unity (health care increases at a greater rate than income), and others reporting income elasticities closer to one. Across OECD countries, healthcare expenditure per capita generally grows 1 to 2 per cent faster than GDP (Przywara 2010). Increases in healthcare expenditure growth in excess of income growth may be the result of several factors, such as increasing public expectations of what the healthcare system can or should deliver, financial frameworks that reward greater levels of activity, and the emergence, adoption and widespread diffusion of new technologies and services.

iii. Developments in medical technology

Empirical studies from a large number of countries have shown that technology is an important supply-side driver of healthcare demand. There are several channels through which technological advancements can increase the demand for health care: expanding the number of treatable conditions; increasing provision of services to individuals who would not undergo a particular treatment otherwise; improving the capacity of the system to treat more patients (e.g. by reducing procedure time, length of stay, or number of hospitalisations); extending the life of patients with life-threating conditions adding more years of healthcare utilisation; intensifying the level of use of technology for the same condition; and generating consumer demand for care. On the other hand, a new technology that substitutes for an existing less effective technology may reduce re-occurrence of the disease, therefore allowing individuals to live in an improved health state and demanding less health care.

iv. Health seeking behaviour

Individual health seeking behaviour may have a significant impact on health status and, ultimately, on the demand for healthcare services. Health-seeking behaviour is defined as ‘personal actions to promote optimum wellness, recovery and rehabilitation’ (Moorhead, Johnson et al. 2018) and covers a spectrum of actions, including health education and awareness, engagement in healthy lifestyles (smoking cessation, healthy dietary habits), and use of preventive healthcare services. Public health, through health promotion and disease prevention programmes, can change societal norms about health-seeking behaviour and consequently influence demand for health care.

v. Health prices and productivity

The price of health care, relative to the general price level, has been identified as a significant driver of healthcare spending growth. A positive effect of relative prices on healthcare spending would support Baumol’s model, which posits that in labour intensive services, such as health care, productivity is lower than in other sectors. However, as wages in low-productivity sectors must keep up with wages in high-productivity sectors, prices for healthcare services will tend to rise faster than other prices.

vi. Healthcare system organisation

Healthcare system characteristics may also influence the demand for health care. The literature has reported comparisons across healthcare systems with different characteristics regarding the share of healthcare expenditures that are publicly financed and regarding methods of provider remuneration. Although there is no consensus, in general, it was found that per capita healthcare expenditure was lower in healthcare systems with a higher share of publicly financed expenditure, possibly because of greater control of healthcare providers in these systems.

5.2 Extrapolation

5.2.1 Projections by the Congressional Budget Office (Congressional Budget Office 2007)

Table A1 presents CBO's projections of healthcare spending regarding the major health care programmes, as a percentage of GDP. These projections were taken from CBO's 10-Year Budget projections. The difference between predicted and real values ranges from 0.0 (2017) to 0.4 (2019) percentage points.

Table A1. CBO's 10-Year Budget projections: Major Health Care Programmes as % GDP

Year	Predicted Values*	Actual Values	Difference Predicted less Actual (percentage points, pp)
2017	6.0%	6.0%**	0.0 pp
2018	6.0%	5.9%***	0.1 pp
2019	6.3%	5.9%****	0.4 pp

*These figures were taken from CBO's June 2017 report An Update to the Budget and Economic Outlook: 2017 to 2027 (Congressional Budget Office 2017).
**These figures were taken from CBO's April 2018 report The Budget and Economic Outlook: 2018 to 2028 (Congressional Budget Office 2018).
***These figures were taken from CBO's budgetary projections that appear in the agency's August 2019 report 'An Update to the Budget and Economic Outlook: 2019 to 2029' (Congressional Budget Office 2019). ****These figures were taken from CBO's budgetary projections that appear in the agency's January 2020 report The Budget and Economic Outlook: 2020 to 2030 (Congressional Budget Office 2020).

5.2.2 Projections by the Office for Budget Responsibility (Licchetta and Stelmach 2016)

Table A2 presents OBR's central projections of public spending on health, as a percentage of the national income. In 2019/20, the difference between the predicted and actual values amounted to -0.4 percentage points.

Table A2. OBR central projections of public spending on health as % of GDP

Financial Year	Predicted Values*	Actual Values**	Difference Predicted less Actual (percentage points, pp)
2017/18	7.3%	7.1%	0.2 pp
2018/19	7.1%	7.1%	0.0 pp
2019/20	7.0%	7.4%	-0.4 pp

*These figures were taken from FSR – January 2017 (Office for Budget Responsability 2017).
**These figures were taken from PESA (Public Expenditure Statistical Analysis), 2020, Table 4.4 – Public sector expenditure on services by function as a per cent of GDP, 1996-97 to 2019-20 (HM Treasury 2020).

5.3 Computed General Equilibrium (CGE) models

5.3.1 Projecting long term medical spending growth on Medicare (Borger, Rutherford et al. 2008)

In this paper, Borger and colleagues prepare 75-year medical spending projections of Medicare in the US. The authors use a dynamic general equilibrium model of the US economy and the medical sector in which the adoption of new medical treatments is endogenous (i.e. determined within the model).

The authors consider an economy with two types of goods and services: medical and non-medical. They are produced using two factors, labour and capital. To provide a framework for representing the relationship between medical innovation and the demand for medical care, health is modelled as a private, non-market commodity. It is produced using a combination of medical goods and services and a non-market input representing the current state of medical knowledge. The latter is a non-traded good which evolves autonomously over time at a constant geometric growth rate.

For the single period model, the consumer problem is represented as a three good demand system. The supply side of the single period model is a profit maximisation problem for two types of firms, medical and non-medical. Prices are determined at the levels that clear output and factor markets. As for the Government, it consumes only non-medical goods and services. Its activity is funded by a lump-sum tax. The authors assume that total government consumption is approximately 20% of GDP, in line with previous analyses performed by the Centers for Medicare & Medicaid Services (CMS).

As an extension of this model, an intertemporal framework was introduced. This extension adds time subscripts to all variables, and consumers have to choose their consumption path. In this model, all prices are interpreted as present values. At any point in time, there is a shadow value for health, and health enters into consumer preferences along with other goods. Following the Ramsey growth model, households maximise their utility, subject to the intertemporal budget constraint. In the spirit of the Ramsey model, capital stock evolves through depreciation and investment and markets for primary factors and output clear in each period.

To simulate these models, authors assigned values to parameters based on 1977 and 1992 US input-output data. However, the model relies on three unobserved parameters: reference period technology share of health output (α_h); elasticity of substitution between medical knowledge and medical care inputs in the production of health (σ_h); and growth rate of medical knowledge (g_z).

The authors used three methods to assign possible values for these key parameters:

- Calibrating the model to a reference period;
- Reconciling the parameter values with demand elasticity estimates from the literature; and
- Estimates developed from a time series method.

Based on these methods, three scenarios were set:

- Low, where α_h=0.6, σ_h=0.45 and g_z=9.6%;
- Intermediate, where α_h=0.9, σ_h=0.4 and g_z=6.3%; and
- High, where α_h=0.95, σ_h=0.2 and g_z=5.0%.

The price elasticity assumed in the high scenario is consistent with the low end of the range estimates, such as the RAND Health Insurance Experience (HIE). In the low scenario, the price elasticity is closer to the international results and implies a stronger rationing effect.

Medical care consumption was measured using the personal health care (PHC) consumption estimate produced by the CMS.

The simulation results show that PHC share of GDP (inclusive of growth attributable to demographic effects) in 2080 will amount to 35%, 45% and 24% under intermediate, high and low scenarios, respectively. Using the federal government's methodology (i.e. CMS OACT), this figure is 41%, which is higher than that implied in the intermediate scenario.

5.4 Cell-based macrosimulation models

5.4.1 The Wanless model (Wanless 2002)

The model developed by Derek Wanless and the Health Trends Review team at HM Treasury (Wanless 2002) generates activity, unit cost, and total cost projections for each year between 2002-03 and 2022-23 and considers three scenarios:

1) Solid progress: individuals are more engaged with their health, life expectancy rises, more appropriate use of the system, higher rates of technology, and more efficient use of resources;
2) Slow uptake: no changes in public engagement, small rise of life expectancy, health status of the population stays constant or deteriorates, lower rates of technology uptake, and low productivity;
3) Fully engaged: high levels of engagement of individuals with their health, life expectancy rises beyond projections, health status improves dramatically, high rates of technological uptake particularly in prevention, and very efficient use of resources.

The following factors affecting activity rates, unit costs, or total costs were incorporated into the model:

- Demographic change:
    - age and sex population projections;
    - mortality rates, which are used to separate projections into projections of decedents and survivors.
- Costs of the five National Service Framework (NSFs) for specific diseases (to meet quality standards): coronary heart disease (CHD), cancer, renal disease, mental healthcare services for adults and diabetes;
- Changes in the age-specific used of care, i.e. healthcare needs;
- Other factors impacting expenditure: waiting times, technological development and productivity;
- Workforce model developed with the Department of Health to estimate staff implications.

As mentioned before, the Review's modelling had three stages:

1) Projecting expenditure to reflect demographic change, but assuming healthcare needs and the quality of care remain constant.
2) Assessing changes associated with the resource implications of meeting the quality standards set out in the NSFs, and changes in age-specific use of care linked to changes in education, income, public expectations or public awareness.
3) Incorporating the impact of certain key drivers of healthcare expenditure that apply to all disease categories and ages (e.g. technological change, productivity gains).

The baseline data was gathered from routine administrative data, such as the Hospital Episodes Statistics (HES) database. Other data, such as GP visits, have been drawn from surveys. The Personal

Social Services Research Unit (PSSRU) at the London School of Economics provided the baseline data and projections of long-term care for those aged over 65.[26]

Using a cell-based projection model, the authors projected total UK healthcare spending as a percentage of GDP of 12.5% in the slow uptake scenario, and of 10.6% in the fully engaged one. For the solid progress scenario, the estimated figure was 11.1%. This represents a rise in the levels of expenditure from £68 billion in 2002-03 to values in 2022-23 of £154, £161 and £184 billion in the fully engaged, solid progress and slow uptake scenario, respectively.

The model estimates that improving quality accounts for around two thirds of the growth rate in each scenario. For example, in all three scenarios, the additional costs of reducing inpatient and outpatient waiting times to two weeks is estimated to be £10 billion a year by 2022-23.

The workforce model estimates that, under the three scenarios, the healthcare workforce might need to increase by over 300,000 over the 20-year period, of which one third corresponds to nurses and over 60,000 to doctors.

Projections for total health spending (per cent of GDP) under the three scenarios (solid progress, slow uptake and fully engaged) are presented in Table A3, as well as the actual (observed) values. Note that projections from the Wanless Report include 1.2 per cent for private sector health spending. The actual figure only includes public sector expenditure. The predicted values in all three scenarios are higher than the actual values. This difference ranges between 2.3 percentage points (fully engaged) and 3.6 percentage points (slow uptake). These differences relate to public sector expenditure only.

Table A3. Wanless Report: total health spending (per cent of money GDP)

	Projections FY 2017/18*	Projections less private sector FY 2017/18	Actual value excluding private sector FY 2017/18**	Difference Projections*** *less* Actual (percentage points, pp)
Solid Progress	10.9%	9.7%		2.6 pp
Slow Uptake	11.9%	10.7%	7.1%	3.6 pp
Fully engaged	10.6%	9.4%		2.3 pp

*These figures include 1.2 per cent for private sector health spending (Wanless 2002).
**This figure was taken from taken from PESA (Public Expenditure Statistical Analysis), 2020, Table 4.4 – Public sector expenditure on services by function as a per cent of GDP, 1996-97 to 2019-20 (HM Treasury 2020).
***We adjusted the projections figure to exclude private sector healthcare expenditure.

5.4.2 The Hippocrates model: Projections of demand for health care in Ireland, 2015-2030 (Wren, Keegan et al. 2017)

The Hippocrates model provides projections of public and private healthcare demand for Irish health and social care services for the years 2015-2030. The model was developed at the Economic and Social Research Institute (ESRI) in a research programme funded by the Department of Health. Projections are provided for a broad range of health and social care services including acute hospital, primary, community, and long-term care.

[26] The PSSRU model is a cell-based macrosimulation with five main parts. The first part estimates numbers of older people with different levels of disability by age, gender, household type/informal care and housing tenure; and creates up to 1,000 population sub-groups or cells. The second part attaches a probability of receiving health and social care services and disability benefits to each cell. The third part estimates total health and social services expenditure, which in the fourth part is allocated to the various sources of funding. A fifth part projects the numbers of social care staff required to deliver the projected services.

Disaggregated administrative data are applied where available, otherwise, more aggregated data and/or survey data are included. Population projections are informed by the 2016 Census of Population and the ESRI's demographic analyses.

The first step in building the model is to estimate utilisation of health and social care services in the base year 2015. To ensure that projections are sensitive to changes in population structure, these estimates are by single year of age and sex, or at as disaggregated a level as the data provides. Healthcare utilisation is measured in terms of activities e.g. a hospital bed day, a home help hour, or a visit to a general practice. Activity rates (AR) for 2015 are calculated by dividing the volume of activity (AV) for each age and sex cohort in 2015 by the population volume (Pop) for each age and sex cohort in 2015.

Formally,

$$A\mathrm{R}(2015)h,s,a = A\mathrm{V}(2015)h,s,a/P\mathrm{op}(2015)s,a$$

In its simplest form the model assumes that, while activity rates in 2015 differ by age and sex cohorts, the activity curves these rates generate remain constant across all projection years. Therefore, activity volume (healthcare demand) for each projection year *t* for activity *h*, sex *s*, and age cohort *a* is calculated as a product of age and sex-specific population projections for that year, and age and sex specific activity rates for 2015. That is,

$$A\mathrm{V}(t)h,s,a = A\mathrm{R}(2015)h,s,a * P\mathrm{op}(t)s,a$$

Total projected demand for a particular service for each year can then be estimated by summing across each age and sex breakdown.

Consequently, in this simple form of the model, all growth in activity is purely a function of the shape of the respective activity curves in 2015 and changes in the size and structure of the population through the projection period. The model assumes that the population in Ireland will continue to grow rapidly and examines two alternative population growth trajectories, referred to as the central population and high population growth projections. These projections are driven by assumptions about mortality, migration, and fertility.

The projections begin with an estimated base population for 2015, which is disaggregated by age (under 1 to 99 and 100+) and sex. For each year, from 2015 to 2030, the population is advanced one year of age using projected age and gender-specific mortality rates for that year. This creates a surviving population for each year that is then adjusted for the level of net migration for that year. A new birth cohort is added to the population in each year, by taking the projected female population and applying the fertility rate applicable to their age group during that year. The total number of births in a year is assumed to be divided between the sexes in the proportions of 51.3 per cent males and 48.7 per cent females, in line with recent experience. Births are then adjusted for infant mortality and migration to form the population under one year of age, which is then added to the surviving population.

The two population growth scenarios emerge from different assumptions about mortality, migration, and fertility rates. Mortality rates are assumed to decrease with gains in life expectancy at birth from 78.4 years for males and 82.9 years for females in 2011 to: a) 82.9 years for males and 86.5 years for females in 2030 (central population growth scenario), and b) 83.2 years for males and 86.8 years for females in 2030 (high population growth scenario). Regarding net immigration, the migration projections contained in ESRI's 2016 Economic Outlook are used. The central (high) population growth scenario assumes an average net immigration of around 9,000 (39,000) per annum until 2021, and around 13,000 (28,000) per annum thereafter. In the central population growth scenario, the fertility rate is assumed to remain unchanged from the 2015 rate of 1.94 over the projection horizon. In the high population growth scenario, the fertility rate rises to 2.1 (the level of fertility at which a population exactly replaces itself from one generation to the next) by 2021, and remains constant thereafter.

Based on the assumptions about mortality, migration, and fertility, the central scenario projects that the population of Ireland will increase between 2015 and 2030 by around 14% to reach 5.35 million. The high population growth scenario projects 440,000 above that of the central scenario for a total of 5.79 million.

In this simple form of the model, activity rates are held constant through the projection period. However, the assumption may be unrealistic. For this reason, the Hippocrates model makes a number of alternative scenarios adjusting the activity rates to reflect alternative hypotheses about the relationship between increased life expectancy and health. The ‘healthy ageing‘ hypotheses are as follows:

1) **Expansion of morbidity** (EM) (Gruenberg 1977): assumes that medical progress will successfully improve survival probabilities for a number of chronic diseases requiring life-long treatment. Therefore, as life expectancy increases, the years spent in ill health and disability also increase.
2) **Compression of morbidity** (CM) (Fries 1980): assumes that healthier lifestyles will decrease or postpone the incidence of a disease until later ages and, because there is an upper limit to human lifespans, the onset of chronic illness and resultant morbidities will be compressed into an ever-decreasing proportion of an individual’s life; and
3) **Dynamic equilibrium** (DE) (Manton 1982): assumes that medical progress will successfully improve survival probabilities. The prevalence of chronic disease will increase, but the severity of the disease and disability will reduce. The total effect will be an increase in the absolute number of years lived in good or mild ill health by an amount equivalent to the increase in life expectancy. This hypothesis has been linked to the ‘proximity to death‘ hypothesis, which posits that closeness to death, rather than chronological age, is the key determinant of increasing healthcare costs.

Because the impact of ageing on healthcare demand in each health and social care sector varies, ‘healthy ageing’ assumptions are included based on the evidence available in each sector. For instance, empirical evidence shows that ‘proximity to death’, as opposed to age, is the key driver of acute care demand. Therefore, in the area of acute hospital care (including public hospital inpatient, day-case, and Emergency Department (ED) services, and private hospital inpatient and day-case services), the most appropriate ‘healthy ageing’ assumption is DE, which assumes that all additional life years are lived in good health or mild ill health. In contrast, because the primary care sector meets most of the increased demand for treating chronic diseases and there is more pessimistic evidence for healthy ageing when chronic disease prevalence is examined, the most appropriate ‘healthy ageing’ assumptions in this sector are EM, and moderate healthy ageing (MHA). The latter falls between expansion of morbidity EM and DE. For a few sectors, such as residential long-term care and home care, mixed evidence supports a wide range of assumptions including both CM and DE. Lastly, for sectors such as outpatient care, maternity services, and speech and language therapy services, data do not support any ‘healthy ageing’ assumptions.

The ‘healthy ageing’ assumptions are applied by treating activity as a proxy for morbidity or disability. In the case of DE, any gain in life expectancy is accompanied by an equivalent reduction in morbidity/disability. For example, if the gain in life expectancy is one year, an 80-year-old in the projection year will have the health status and, therefore, activity rate of a 79-year-old in the base year. In the case of EM, there will be no shift in activity rates. In the case of CM, the gain in health status is assumed to exceed the gain in life expectancy by 50%, while in the case of MHA, the gain in health status is assumed to be one half of the gain in life expectancy and the activity rates are adjusted accordingly. Formally, activity rate shifts enter the model as follows:

$$AR(t)h{,}s{,}a = AR(2015)h{,}s{,}a - k*\Delta LE(t{,}2015)s{,}a$$

where $AR(t)h{,}s{,}a$ represents the activity rate in year *t* for service *h*, sex *s* and age *a* adjusted based on shifting the baseline activity rate to reflect the activity rate of a younger cohort in proportion to life expectancy increases ΔLE. The parameter *k* represents the relationship between life expectancy increases and gains in health status. Where *k=0*, no shift takes place which models the EM hypothesis, whereby gains in life expectancy are not matched by gains in health status. The MHA assumption is applied by setting *k=0.5*, while the DE assumption is modelled by setting *k=1*. Any *k>1* represents the CM hypothesis. Authors set k=1.5 for modelling CM.

In addition, a range of assumptions about future demand were made by adjusting activity rates to reflect unmet need or demand for care. The unmet-need adjusted activity rate equals the baseline (met) activity volumes plus a volume of unmet need or demand for services in the base year.

Formally,

$$ARum\_adj(t)h{,}s{,}a = AR(t)h{,}s{,}a + ARum(2015)h{,}s{,}a$$

where

$$ARum(2015)h{,}s{,}a = AVum(2015)h{,}s{,}a/Pop(2015)s{,}a$$

$AVum(2015)h{,}s{,}a$ and $ARum(2015)h{,}s{,}a$ represent the volume and rate of unmet need, respectively for base year 2015 for service *h*, sex *s*, and age *a*.

The approach to estimating volumes of unmet need differs across services, and is heavily influenced by the type and availability of data (no unmet need or demand was estimated for private hospitals, pharmaceuticals in the community, or ED services). For instance, where survey data are utilised, self-reported levels of unmet need (e.g. for GP services) are converted into a measure of activity (e.g. a GP visit). For other services, administrative waiting list data are used to measure the volume of unmet demand (i.e. the number of people on a waiting list for a particular service), and not necessarily total unmet need.

In summary, the Hippocrates model provides projections of healthcare demand in Ireland for the years 2015-2030 by examining a number of alternative scenarios for population growth. A projection based on the central population growth scenario, and the assumption that age and sex specific activity rates remain constant over the projection period, serves as the comparator scenario. Central and high population growth assumptions are combined with (sector specific) healthy ageing and unmet need assumptions to develop a preferred projection range by sector. For instance, three scenarios are examined for public hospitals inpatient and day cases: central population growth with DE assumption about healthy ageing and no assumptions for unmet need; high population growth with DE assumption about healthy ageing and no assumptions for unmet need; central population growth with DE assumption about healthy ageing and high unmet need.

Table A4 to Table A6 present the projections for the three main hospital services in the public sector: total number of inpatient and day case discharges (Table A4), outpatient department attendances (Table A5) and emergency inpatient discharges (Table A6). The authors predict fewer inpatient discharges compared to the actual values, but the difference is small. As for outpatient department attendances, there were fewer attendances compared to those predicted.

Table A4. Total inpatient and day cases discharges ('000)

Year	Predicted Values*	Actual Values**	Difference Predicted less Actual
2017	1,708	1,719	-11
2018	1,725	1,737	-12
2019	1,743	1,771	-28

*These figures were taken from Projections of demand for health services in Ireland, Table A7.1 (Wren, Keegan et al. 2017).
**These figures were taken from Activity in Acute Public Hospitals in Ireland, 2020 Annual Report, Table 1.1 (Healthcare Pricing Office 2021).

Table A5. Outpatient department attendances ('000)

Year	Predicted Values*	Actual Values**	Difference Predicted less Actual
2017	3,395	3,288	107
2018	3,439	3,336	103
2019	3,483	3,355	128

*These figures were taken from Projections of demand for health services in Ireland, Table A7.1 (Wren, Keegan et al. 2017).
**These figures were taken from Health in Ireland, Key Trends 2021, Table 3.1 (Department of Health 2021).

Table A6. Emergency inpatient discharges ('000)

Year	Predicted Values*	Actual Values**	Difference Predicted less Actual
2017	429	434	-5
2018	435	443	-8
2019	440	448	-8

*These figures were taken from Projections of demand for health services in Ireland, Table A7.1 (Wren, Keegan et al. 2017).
**These figures were taken from Activity in Acute Public Hospitals in Ireland, 2020 Annual Report, Table 1.1 (Healthcare Pricing Office 2021).

5.5 Microsimulation models

There are several papers that outline the main features of microsimulation approaches (e.g. Zaidi and Rake (2001), Li, O'Donoghue et al. (2014)) and papers that offer an in-depth survey and review of healthcare dynamic microsimulation models (e.g. Spielauer (2007), Lymer, Brown et al. (2009), Zucchelli, Jones et al. (2012)). Zaidi and Rake (2001) draw 12 lessons for researchers about constructing a model of this nature. These include recommendations on: establishing priorities and clear objectives of the exercise, the treatment of time and the choice of timeframe for the model, determining baseline data to populate the microsimulation, and techniques for model validation among others. Other authors deal with more specific problems; for example, Dekkers (2015) focuses on the choice of static versus dynamic ageing techniques and discusses issues to address when selecting the type of microsimulation model to construct.

5.5.1 RAND Future Elderly Model (FEM) (Goldman, Shekelle et al. 2004)

In this section we provide additional detail of the Future Elderly Model (FEM). As mentioned, the FEM involves three phases:

1. ***Individual trajectories for*** *a number of health conditions and disability statuses:*

The outcome measure is based on data from pairs of consecutive interviews, and only data on those who did not report a specific condition at the initial interview were included, in order to model the likelihood of developing the condition.
The FEM then predicts the health conditions and functional status of the baseline sample for the next year (reweighting to match the health status trends from the National Health Interview Survey (NHIS) and the Census population projections), treating all health states as 'absorbing'.

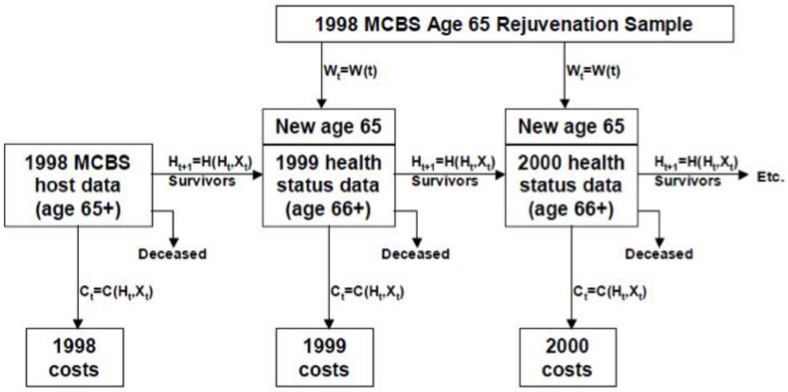
2. ***The rejuvenation sample*** *ensures that the data remains representative of the population aged 65 years or over*

Every year there is a rejuvenation of the sample that is weighted in accordance with the previous year's prevalence rates of health conditions among 65-year-olds, and to ensure that the sum of weights for age 65 in the simulation sample equals the year population of 65-year-old individuals.

3. ***Projections*** *of future Medicare and total healthcare expenditures based on the demographic and health characteristics of the population.*

The cost estimations were based on pooled weighted least squares regressions, with total Medicare reimbursement and total healthcare reimbursement as the dependent variables; and health status measures, self-reported disease categories, and interactions of health measures and disease conditions as the independent variables. The model was calibrated to replicate the total healthcare and Medicare expenditures for the elderly sample, represented by the Medicare Current Beneficiary Survey (MCBS).

The FEM started with data from the MCBS, which includes a nationally representative sample of aged, disabled, and institutionalised individuals. As the initial sample ages, it becomes less representative of the entire over-65 population; thus, the authors rejuvenate the sample yearly with a newly entering cohort of 65-year-olds. Figure A1 presents an overview of the FEM model.



NOTES: 1. C = costs; C_t = costs in a given calendar year; H = health status; H_t = health status during the year of the interview; W = a relative weight; X_t = demographic controls. 2. Costs are predicted in constant (1998) dollars and assume a level of treatment and technology as it existed in the 1990s.

Figure A1. Overview of the FEM Model[27]

To develop the model, data are needed on the same individual for at least two waves. Only individuals without a health condition are entered in the first health transitional model iteration.

5.5.2 Population Health Model (POHEM) (Hennessy, Flanagan et al. 2015)

The Population Health Model (POHEM) involves six steps, described in section 0. Step 2 ('Initialisation') can be done in two different ways: using an initial population or creating a synthetic population. Both approaches have advantages and disadvantages.

While using an initial population directly from a survey has the benefit of potentially providing a wide range of individual characteristics from which the multivariate joint distribution of these variables is empirically based, and may draw from a large number of respondents, there are some important disadvantages. The first one regards to the extent of heterogeneity in the starting population, which is limited by the initial size of the sample and by any imputation done for simulation purposes. Another disadvantage is that historical information on the duration of a condition or exposure may be unknown (e.g. cumulative pack years smoked) and needs to be imputed.

The second approach, using a synthetic population, has the advantage of covering individuals' full life course, including risk exposures, from birth to death. The main challenge is a lack of historical information about risk exposures (e.g. smoking).

POHEM has been applied to several health conditions and we highlight the following two:

- **Cancer model**

Will, Berthelot et al. (2001) summarise three policy relevant examples: cost-effectiveness of chemotherapeutic interventions for lung cancer; an analysis of the impact of reduced length of stay following breast cancer surgery; and a cost-effectiveness analysis of the provision of 'preventive' tamoxifen for women in Canada at risk of developing breast cancer.

[27] Source: Goldman, D. P., et al. (2004). Health status and medical treatment of the future elderly, RAND Corporation. Available from: https://www.rand.org/pubs/technical_reports/TR169.html. Reproduced with permission from the RAND Corporation.

- **Osteoarthritis model**

Kopec, Sayre et al. (2010) use POHEM to develop a population-based simulation model of osteoarthritis (OA) in Canada that can be used to quantify the health and economic burden of OA under a range of scenarios (different combinations in the OA risk factors and treatments).

5.5.3 Australian Population and Policy Simulation Model (APPSIM) (Lymer, Brown et al. (2011) and Lymer, Brown et al. (2009))

The Australian Population and Policy Simulation Model (APPSIM) is a closed, stochastic, cross-sectional dynamic population microsimulation model that provides snapshots of the population characteristics and government programmes as at June each year, from 2002 through to 2050, and operates in discrete time. APPSIM simulates all of the major events that happen to Australians during their lifetime and has a health module. The ageing population was the motivation for the development of a health microsimulation model.

APPSIM is made up of a series of modules that are processed sequentially. Starting at time, it moves clockwise through the modules sequentially starting with disability, then demographics, household formation, etc., to the last module, which is the health module (see Figure A2). Within each module, the individual in the base data is subject to series of transition equations, which simulate if the event occurs or not. As the simulation steps through time, the probability of a person changing from one state to another is considered, and Monte Carlo simulation is used in each module to determine if the events actually occur to the individual.

Figure A2. Overview of APPSIM framework[28]

The main objective of the health module is to provide projections of healthcare expenditure under different demographic and policy scenarios. The health module focuses on adults, all individuals aged 15 years and over, as there are no longitudinal data in Australia on the health of younger children. This module is made up of eight sub-modules, including four health risk behaviours, which are processed sequentially (physical activity, alcohol consumption, smoking status, obesity, self-assessed health status, private health insurance, service use and expenditure).

[28] This diagram was reproduced from Lymer, S., et al. (2011). Modelling the health system in an ageing Australia, using a dynamic microsimulation model, University of Canberra, National Centre for Social and Economic Modelling.

These interact with each other and also become input parameters for the modelling of health status. The health status module is represented by self-assessed health status (SAHS). The model applies ordinal logistic regressions to determine the probabilities of having each level of SAHS. Monte Carlo simulation used to allocate the individual's health status and, subsequently, their transitions. Transition probabilities in health status are calculated using a generalised linear mixed model.

Socioeconomic factors such as education, income, and labour force status (which are modelled external to the health module) are input parameters to both the health risk factors and health status.

In a later stage, health status becomes an input parameter to healthcare service usage that models separately medical, hospital, and pharmaceutical sectors with average values of services by age-sex, health status and health insurance groups, which is in turn used in estimating healthcare expenditure.

The primary data source for the modelling within the health module was the Household, Income and Labour Dynamics in Australia (HILDA) survey. Due to the longitudinal nature of HILDA, it has allowed modelling transition probabilities of individuals from one health state to another over time. The modelling has assumed that the relationship between certain age groups and behavioural responses will be the same over time. For example, 20 year olds in 2040 are assumed to have the same behavioural responses as 20 year olds in 2006.

The primary source of data for the APPSIM general model is the 2001 Australian Census (basefile), which does not include any health data, so initial imputation of health risk behaviours and health was required by means of logistic and generalised ordinal logistic regressions.

Validation is an important part of the model several and takes several forms:

1. Sensitivity analysis allowing the establishment of the impact of specific parameters on the model output;
2. Comparison of characteristics within the model against credible exogenous totals and distributions; and
3. Computation of uncertainty surrounding the estimates is an important element of validation.

The APPSIM has some limitations. First, and due to data limitations, imputation was required for health status for individuals in the basefile and for the transition equations. Second, the modelling has assumed that the relationship for certain age groups will be the same over time. Finally, it ignores children and those living in non-private dwellings. The latter group is likely to be linked to high healthcare costs.

5.5.4 NCDMod: A Microsimulation Model Projecting Chronic Disease and Risk Factors for Australian Adults (Lymer, Schofield et al. 2016)

The NCDMod, which is a major redevelopment of HealthAgingMod, is a purpose-built microsimulation model that simulates multiple chronic diseases and associated risk factors of Australians aged 20 years or over. NCDMod undertakes medium term projections, from 2010 to 2025, of impacts of demographic changes and impacts of effective interventions to address health risk factors and health conditions.

NCDMod can be used to estimate, under given scenarios, (i) the incidence of diabetes and cardiovascular diseases (CVD), (ii) total healthcare expenditure and specific costs of interventions considered, and (iii) years of life lost and disability adjusted life years. In addition, and combined with the Health&WealthMod2030, this model can be used to estimate the potential impact of health interventions on the long-term costs of ill health leading to unplanned retirement. Finally, NCDMod can also be used to compare estimates of potential healthcare costs savings from disease interventions.

NCDMod has four main components, depicted in Figure A3:

1. **Base population (basefile)**

NCDMod is based on the 2005 National Health Survey (NHS05), which includes a set of variables such as health status, chronic diseases, health risk behaviours, and socio-demographic characteristics. The basefile was reweighted through a generalised regression-reweighting algorithm to modify initial survey weights to represent the more current 2010 Australian population.

To facilitate simulation of chronic diseases, some enhancements to the basefile were included, such as converting age from categories to single years through Monte Carlo simulation, BMI groups and blood pressure categories converted to continuous values, imputation of total cholesterol, and parental history of diabetes.

2. **Incidence models for chronic disease and risk factors**

The statistical transition models used had two sources: (i) literature on previously studied transitions, and (ii) in-house modelling. From the literature, authors used, among other studies, the Framingham risk equations for acute myocardial infract, stroke and cardiovascular deaths (Anderson, Odell et al. 1991), the equations from Wilson, Anderson et al. (1994) that model the cholesterol trajectory, and the work by Wu, Ware et al. (1980), which model the systolic blood pressure trajectory for individuals not receiving blood pressure treatment .

In-house modelling was based on the AUSDIAB data (cross-sectional, national, population-based survey), and it modelled changes in BMI over time.

3. **Healthcare expenditure modelling**

Total healthcare expenditure focused on government expenditure and was inclusive of health goods and services such as hospitals (both public and private), primary health care, and community health. Healthcare expenditure was modelled based on diabetes status, CVD event, and BMI group.

4. **Population projections**

To account for population growth, the Australian Bureau of Statistics (ABS) population projections were used.

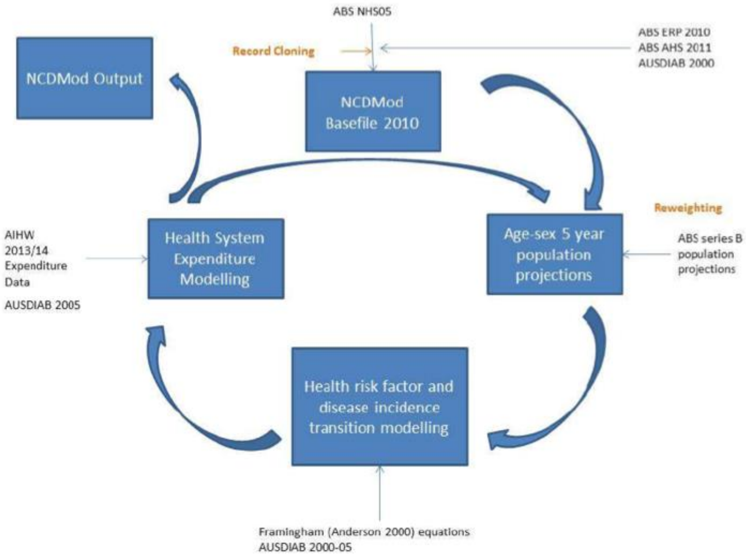


Figure A3. Overview of NCDMod framework[29]

To validate the model, i.e., assess if the model output is reasonable for the outline purpose, several activities were performed, such as clinical review of model specification for face validity and comparison the model's output with external data when available. Before validation, the research team decided that all results within 10 per cent of the survey estimates (which are also subject to error) would be deemed acceptable.

The NCDMod has some limitations. First, it focuses only on two chronic diseases (diabetes and CVD) and their associated risk factors (emphasis on obesity). Second, the results might be underestimated, since the basefile excludes individuals living in non-private dwellings (hostels or nursing homes), which are the people in the poorest health. Third, the transition equations from the literature are based on populations from another country with different levels of risk factors, which is problematic (and reflected in the validation process). Finally, a technical limitation: the random variability present due to the use of Monte Carlo simulation methods.

5.5.5 A dynamic micro-simulation model of outpatient healthcare expenditure in France (Geay, de Lagasnerie et al. 2014)

This is a dynamic microsimulation model for outpatient healthcare expenditure in France, which projects healthcare costs in the long run (from 2008 to 2032). Outpatient healthcare expenditure is estimated using a two-part model, and aims to examine the impact of ageing on expenditure.

The baseline dataset is representative of the metropolitan population of France in 2008, in terms of age, gender, social affiliation, and household size and comes from two sources:

1. The Social Protection and Health Survey from the Institute for Research and Information in Health Economics that provides the social and health characteristics of each individual (four timepoints between 2002 and 2008).
2. The National Health Insurance Fund that provides the level of outpatient healthcare expenditure for each individual during the year.

[29] This diagram was reproduced from Lymer, S., et al. (2016). "NCDMod: a microsimulation model projecting chronic disease and risk factors for Australian adults." International Journal of Microsimulation **9**(3): 103-139. This article is distributed under the terms of the Creative Commons Attribution (CC BY) License.

The model computes the health status of each individual by: (i) constructing an individual health stock from the subjective self-assessed health; (ii) using a more objective measure of health conditions through information about self-reported diseases; and (iii) using the social status to control for the reporting bias.

The health status of each individual is simulated by running a first Markov transition process between three states: two non-absorbing (good-health or ill-health) and one absorbing state (death). The model uses dynamic ageing through the estimation of health status transition probabilities in discrete time as the data are only available every four years.

Then, after taking into account the health status of the individual, the authors link in outpatient healthcare expenditure by means of a two-part model. First, a Probit model estimates the probability of consuming outpatient health care. Second, a generalised linear model estimation is run on outpatient healthcare expenditure to estimate the level of consumption. The authors validate the model using the official population projections.

The final goal for this model is to identify expenditure trajectories at an individual level and shed light on the redistributive effect of healthcare insurance system. For this purpose, the model is adapted to fit in the DESTINIE 2, a microsimulation model of the National Institute of Statistics and Economic Studies. This enables the model to simulate life pathways, including employment, as well as accounting for other variables in the simulation of healthcare expenditure and in the computation of transition probabilities.

5.5.6 SAGE Model: Dynamic Microsimulation Model for Britain (Zaidi and Rake 2001)

The SAGE model, a dynamic microsimulation population model for Britain, is a full population model where individuals are aged dynamically, and was developed to analyse the implications of population ageing for pensions, health, and long-term care needs. The objective of this model is to provide projections to inform the development of social policy in Britain for the XXI century.

The SAGE model involves several processes: mortality, education, fertility, partnership formation and dissolution (cohabitation and marriage), labour market participation, earnings, pension accumulation and income in retirement, health, disability and need for care, and support networks and supply of informal care.

The SAGE model is designed as a modular structure, which grants flexibility and allows different elements to be modified independently. It is a full population model, rather than a single cohort, where individuals are aged dynamically, allowing future states to evolve, depending on the previous characteristics of individuals and families. The population is closed with respect to partnership and parenthood (i.e. partners/parents cannot come from outside the defined population), and a partnership market is implemented for marital and cohabiting relationships.

The baseline data were derived from the 1991 Census of Great Britain. It also used the British Household Panel Survey, the Quarterly Labour Force Survey, and the ONS Longitudinal Study. When panel data do not cover all the information needed, then cross-sectional surveys such as the General Household Survey were used.

5.5.7 Population Ageing and Care Simulation model (PACSim): baseline dataset and model construction (Kingston and Jagger 2017)

The Population Ageing and Care Simulation model (PACSim), a discrete-time dynamic microsimulation model, aims to project the health and care needs of the English population aged 65 years and over to

2040. It also assesses the impact of interventions (i) to reduce risk factors, (ii) prevent diseases, and (iii) and treatments to slow down progression to disease and disability.

The baseline population was constructed using three longitudinal studies: Understanding Society, the English Longitudinal Study of Ageing (ELSA), and the Cognitive Function and Ageing Study II (CFAS II). To estimate the population aged 65 years and over to 2040, the baseline population of PACSim is individuals aged 35 and over. The variables included in PACSim comprise socio-demographic, health behaviours, diseases and geriatric conditions, and dependency using a time-based measure that incorporates the intensity of care. The basefile was reweighted up to the English population in 2014 (base of the projections and gathered from ONS) and cloned so that multiple individuals had unit weights. To ease computing power and time, a 1% random sample was selected as the base population. Missing values were imputed using the chained equations method (White, Royston et al. 2011).

Most of the diseases included are chronic and, therefore, only incidence (transition to disease) was estimated; an exception was made for depression, recovery for vision and hearing impairment, as well as recovery from mild cognitive impairment to normal cognition. For these cases, the probability of recovery was estimated. Transition probabilities were computed using ELSA's follow-up waves. For physical health, transition probabilities were approximated using fitting models to the baseline data, due to lack of suitable data to model transitions.

PACSim uses a discrete time approach with monthly transition probabilities for each stochastic characteristic (over the period January 2014 to December 2042). Using monthly transition probabilities minimises biases arising from competing events, better accounts for non-linearity over a longer period of time, and it allows events to happen more closely and multiply within a year.

The outputs of the model for each year are (i) prevalence and absolute numbers with each disease by age group and sex; (ii) prevalence and absolute numbers with multi-morbidity; and (iii) years lived with individual diseases, multi-morbidity, and dependency.

PACSim was validated using external sources. First, the age groups' time-trends were compared with ONS 2014-based population projections. The results show that PACSim well represented the time-trends. Second, the age and sex specific prevalence of stroke, diabetes, current smoking, overweight, and obesity from PACSim were compared with those from the Health Survey for England 2014. In general, there was a good agreement, apart from the prevalence of obesity, where PACSim estimates were lower for men aged 35-64, and for women of all ages.

The main strength of this model is that it accounts for a large number of chronic diseases, enabling a realistic projection of the future burden of multi-morbidity. However, the model has some limitations. Firstly, morbidities are self-reported, with the exception of dementia and cognitive impairment. Secondly, the transition rates were based on consecutive waves of each survey, which means a time period of 2 years. A longer period would provide more precise estimates of coefficients in the transition models. Thirdly, transitions between states were assumed independent over time. Finally, the model does not provide confidence intervals (Kingston, Robinson et al. 2018).

Recently, Kingston, Comas-Herrera et al. (2018) used the PACSim to project the number of people aged 65 years or older in England, and the years lived in older age requiring care at different intensities.

5.6 Machine Learning

As ML algorithms typically require large datasets from which to form predictions, the methods are generally not used where only a limited number of observations are available. However, they have been successfully used to answer specific questions about healthcare demand. For example, Qiu, Luo et al. (2020) used ML to predict demand of cardiovascular admissions, using environmental exposure as predicting factor. The authors used ML techniques to predict hospital demand using the data on admissions and the air quality data from China, in the period from 2015 to 2017. They compared six different ML algorithms (logistic regression, support vector machine, artificial neural network, random forest, light and extreme gradient boosting) and used a variety of statistics to evaluate the algorithms (among others accuracy, sensitivity, specificity, precision). They found the gradient boosting algorithm outperformed the others, and was considered a useful decision-making tool for resource management. A similar study was undertaken for stroke admissions by Chen, Li et al. (2019).