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**Drivers of Health Care
Expenditure: Final Report**

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Drivers of health care expenditure: Final report

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Background to series

CHE Discussion Papers (DPs) began publication in 1983 as a means of making current research material more widely available to health economists and other potential users. So as to speed up the dissemination process, papers were originally published by CHE and distributed by post to a worldwide readership.

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Abstract

Since the NHS was established in 1948, growth in health care expenditure (HCE) has outpaced the rise in both GDP and in total public expenditure. Known drivers of HCE growth include demographic factors, income and wealth effects, technology and cost pressures. To identify the challenges and opportunities for developing a model of healthcare demand, this report addressed two research questions:

1. What are the drivers of past trends in health care expenditure and how much has each of the drivers contributed to past increases in expenditure?
2. How much has each type of service contributed to past trends in health care expenditure and why have there been different trends for different types of care?

We set out a conceptual framework for understanding drivers of HCE, placing it in the broader context of underlying drivers of demand and macroeconomic trends. We reviewed studies from higher-income countries published over the last decade, and analysed datasets compiled in-house of cost and volume of care by different settings. We linked data on HCE trends to relevant, setting-specific evidence from the literature review.

We identified 52 studies using aggregate data and 54 individual-level studies. The relative contribution of different drivers could not be quantified due to heterogeneity in study methodologies. Aggregate studies using longer panels of data show that the relationship between HCE and its drivers is non-linear, varies over time and varies cross countries. These studies mostly find a strong, positive relationship between HCE and technological progress. Individual-level studies usually rely on observational, non-experimental data from administrative databases, such as claims data or registers, or on survey data or cohort studies. Trends in HCE from 2008/9 to 2016/17 reveal that the largest rises were in high cost drugs (231%), chemotherapy (113%) and attendances at A&E (59%) or outpatient departments (57%). Most evidence on the drivers of HCE related to hospital care, but we found no studies explaining the factors behind the rise in expenditure on chemotherapy or high cost drugs.

We conclude by presenting four lessons that could inform decisions on building a projections model of health care expenditure.

Contents

Acronyms

A&E	Accident and emergency (department)
ACA	Affordable Care Act
BMI	Body mass index
CC	Community Care
CCG	Clinical Commissioning Group
CKD	Chronic kidney disease
D&T	Diagnostics and therapeutics
ED	Emergency department
EoL	End of life
FCE	Finished consultant episode
FYFV	NHS Five Year Forward View
GDP	Gross domestic product
GP	General practitioner
GPPS	GP patient survey
HBC	Hospital based care
HCE	Health care expenditure
HRG	Healthcare resource group
LE	Life-expectancy
LMIC	lower- or middle-income country
LTC	Long term care
LTCE	LTC expenditure
MH	Mental health
NHS	National Health Service
OECD	Organisation for Economic Co-operation and Development
PC	Primary Care
PCA	Prescription cost analysis
PCT	Primary Care Trust
POHEM	Population health model
PSSRU	Personal Social Services Research Unit
RC	NHS Reference Costs
RDNA	Regular Day and Night Admissions
SHARE	Survey of Health, Ageing and Retirement in Europe
TTD	Time-to-death
WP	Work package

Introduction

Ever since the NHS was established in 1948, growth in health care expenditure (HCE) has outpaced the rise in both GDP and in total public expenditure [1]. Year-on-year rises in the real value of HCE are thought to be one of the greatest challenges to long-term fiscal sustainability [2]. Known drivers of HCE growth include demographic factors, income and wealth effects, technology and cost pressures [3].

Tackling the drivers of demand is an enduring policy concern. A key aim of the NHS Five Year Forward View (FYFV) Next Steps was to "reduce avoidable [healthcare] demand and meet demand more appropriately" [4], primarily through service transformation via the New Models of Care [5]. With its 10-year forward view, the NHS Long Term Plan reinforces the need for new service models but also advocates a more radical approach to moderating demand through upstream prevention and tackling health inequalities [6]. The Plan recognises that return on investment is a long-term goal, for two reasons. First, some factors that drive demand are intractable and may only be amenable to change in the long-run (such as entrenched levels of unmet need). Second, other factors that drive demand for HCE are beneficial in themselves (e.g. longer life expectancy, technological innovations). It is also important to understand how expenditure and activity in other sectors, such as social care, may influence HCE.

Evaluations of the drivers of the demand for health care typically infer demand from measures of activity and/or expenditure. However, this captures only 'expressed' demand that differs from 'true' demand because of unexpressed or unmet need (i.e. latent demand). In addition, it is informative to distinguish the elements of expressed demand that are potentially avoidable, i.e. which drivers are amenable to change.

To quantify long-term healthcare spending projections, there is a need to understand what drives past trends in activity and expenditure and how these may change in future. This study addresses these issues by undertaking a rapid review of the drivers of past trends in health care expenditure (HCE) and an analysis of in-house databases to quantify variations in health care expenditure, volume of activity and unit cost. Where possible, we explore how drivers vary by setting. We then identify the steps needed to develop an aggregate model of demand for health care, note the gaps in the evidence base and consider how drivers may change in future.

Aims and objectives

The study seeks to address two research questions, but we also consider future drivers of HCE.

1. What are the drivers of past trends in health care expenditure in terms of demographic change, technology, rising expectations, pay, etc. and how much has each of the drivers contributed to past increases in expenditure?
2. How much has each type of service, such as primary care, pharmaceuticals, emergency secondary care, elective secondary care, etc., contributed to past trends in health care expenditure and why have there been different trends for different types of care?

Conceptual framework

In identifying the drivers of health care expenditure we have undertaken a rapid literature review. This review is not restricted to particular health care systems and aims to identify relevant studies that have considered drivers of expenditure irrespective of the funding and organisational constraints within which the studies were situated (though we excluded studies from lower- or middle-income countries (LMICs)). However, it is important to recognise that, in part, the purpose of

this study is to help inform planning decisions relevant to meet future demand within the context of the NHS [6, 7]. The delivery of health care in the UK is synonymous with the publicly funded NHS, which accounts for by far the greatest proportion of health care provision, with the exception of dental care, for which private provision has grown. Overall, privately-funded health care is small relative to publicly funded care and we are concerned primarily with demand for the latter.

Almost all (around 98%) [8] of financing for the NHS is via conventional income and expenditure taxes including National Insurance. The small remainder is from patient contributions limited to a few items such as dental care, prescription medicines and eye tests. The broad functional split of expenditure is between secondary care, often termed `hospital and community health services' (covering inpatient, day cases and outpatient care), and primary care, usually termed `family health services' (the provision of general medical practice or ambulatory care) and prescribing by general medical practitioners. A small proportion of expenditure is used for non-NHS provision of services [9].

Financing for the NHS is largely determined by Government Spending Reviews, which are influenced by government expenditure limits (via tax and national insurance receipts, and borrowing), political will and public pressure. As such, the NHS is required to manage and organise the supply of health care under a fixed budget. With effectively zero co-payment, access to health care is essentially free at the point of use and demand is not explicitly constrained by price. Instead, the NHS has traditionally relied on a gatekeeping role of primary care physicians together with waiting lists to manage access, particularly to hospital-based treatments. Accordingly, while the NHS faces supply pressures from the constraint of operating under an overall budget, demand is largely determined by population need for health care. Understanding the drivers of need and how these might change in the future are prerequisites to informing levels and distribution of future health care spending.

One approach to determining future health care need is to measure need directly via underlying levels of population morbidity. This would entail measuring the incidence, prevalence and severity of morbidity that is amenable to health care intervention. The cost of treating morbidity would then need to be determined on the basis of a defined package of care efficiently delivered. From these estimates the total cost of treatment could be determined assuming all individuals presented for treatment and were appropriately diagnosed. Such an approach is clearly dependent on having access to extremely rich epidemiological data on individuals, or representative samples thereof, with broad coverage of the population and detailed morbidity measures. Currently available data prevent such an approach being reliably taken forward.

A more pragmatic approach, one that largely has been adopted in the literature attempting to determine the drivers of health-care need [10] and the one we follow, is to rely on past expenditure as a proxy for need. Since health care expenditures are influenced by the constraints of the funding system adopted (private, public, insurance-based systems) the observed relationship between drivers of need and expenditure may also be influenced by the particular funding system. This may be particularly problematic if, due to macroeconomic pressures, it is the funding system, rather than need, that drives expenditure. To place this issue in context, we review the recent experiences of the UK in terms of overall economic activity, public expenditure and health care expenditure in the next section. Whereas there has been a period of very restrained economic growth, health expenditure has maintained a consistent positive trend, which offers some reassurance that expenditure is responding to increasing need.

It can be expected that macroeconomic factors will influence the strength of the relationship between drivers and expenditure, rather than the type of drivers. A focus on expenditure also raises issues around disentangling supply-side determinants of expenditure from demand-side

determinants at a disaggregated level. This is particularly relevant when considering data collected across a number of health care providers, where variation in local policies and practices may well lead to differences in costs of procedures and hence expenditures. Identifying the independent contribution of the drivers of demand in such circumstances can be challenging.

As indicated above, evaluations of the drivers of the health care expenditure typically assume, implicitly, that demand can be inferred from measures of expenditure and activity. However, this captures only **'expressed'** demand, which may not reflect 'true' demand for several reasons. Below, we set out different types of demand. These are not mutually exclusive, but help to clarify the different dimensions of demand.

1. '**Latent'** demand is unexpressed need for (formal) health care and so is not reflected in concurrent activity or expenditure. This can arise because of demand or supply side issues.
    a. Demand-side factors include informational asymmetries e.g. the patient does not access health care because she is unaware of her undiagnosed disease, and/or is unaware of available treatments. There are also 'softer' factors such as fear of receiving a diagnosis or undergoing treatment, or time pressures that delay the decision to utilise care.
    b. Supply-side factors, such as lack of access to health and care services, can be due to:
        i. Capacity constraints: these arise when the supply of services is insufficient.
        ii. The absence of services, such as technologies for treating currently incurable conditions.[1]
        iii. Failures of the principal-agent relationship, such as the failure of the doctor to refer the patient for further investigations, or to prescribe medication when clinically indicated.
2. **Avoidable** demand can arise if latent demand is subsequently expressed later in the disease pathway, e.g. an individual presents with late stage cancer. In addition, some expressed demand for health care is potentially avoidable if it arises because of behavioural risk factors (such as smoking, physical inactivity, diet or substance misuse).
3. **Displaced** demand includes demand that is displaced in time – perhaps through the lack of early intervention - or space (geographically). Spatial displacement refers to care in inappropriate settings, such as delayed discharges.
4. In general, expressed demand must be mediated by supply in order for utilisation to occur. As noted above, this may lead to suboptimal utilisation but can also lead to **supplier-induced demand (SID)** such as over-diagnosis or overtreatment, e.g. clinically unnecessary investigations or treatment resulting from screening programmes. As referral and treatment thresholds can also vary, such as the propensity to admit A&E patients to hospital, reducing unwarranted variation from 'best practice' has potential to reduce SID.

More broadly, the demand for health care can be conceptualised as a **derived** demand for 'good health', i.e. as a capital stock in which individuals invest [12]. The other types of demand can be seen as expressions of this decision (or not) to invest in a health stock. This also offers a framework for understanding how prevention and public health can influence drivers of expressed demand for health care.

In general, studies that investigate the drivers of health care expenditure or healthcare utilisation rarely consider or distinguish the underlying types of demand. However, whether the aim of a model is to project future expenditures or to understand the potential effects of policy interventions, failure to recognise that demand is multifaceted may ultimately lead to poor decision making.

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[1] Arguably, demand or need cannot be defined in relation to HCE in these circumstances [11]

The macroeconomic context

Expenditure on health care in England is primarily public expenditure. Public expenditure is limited in the long run by the willingness of government to tax and the ability of taxpayers to pay. Few economies experience overall public expenditure of more than 50% of their national output (GDP) and if health care absorbs an increasing proportion of public expenditure, other areas of expenditure such as social welfare spending, defence and education will have to be reduced proportionately.

The financial crisis that began in 2008 is well-documented to have had a serious effect on economies around the world and is associated with reduced output and growth. In particular, the years around the crisis saw output as measured by the total value of goods and services, actually decline [13].

In the 10 years since the onset of the crisis, there has been economic growth. The overall value of output of the UK economy in 2017 was approximately £2044bn. The estimate for 2018 is £2100bn which, compared to 2008, represents an increase of around 33%. Price inflation has been modest and amounts to approximately 18% over the 10 years. Overall *real* GDP, after accounting for the timing of the price changes, grew by approximately 13% over this last 10 years. The underlying figures are depicted in Figure 1.
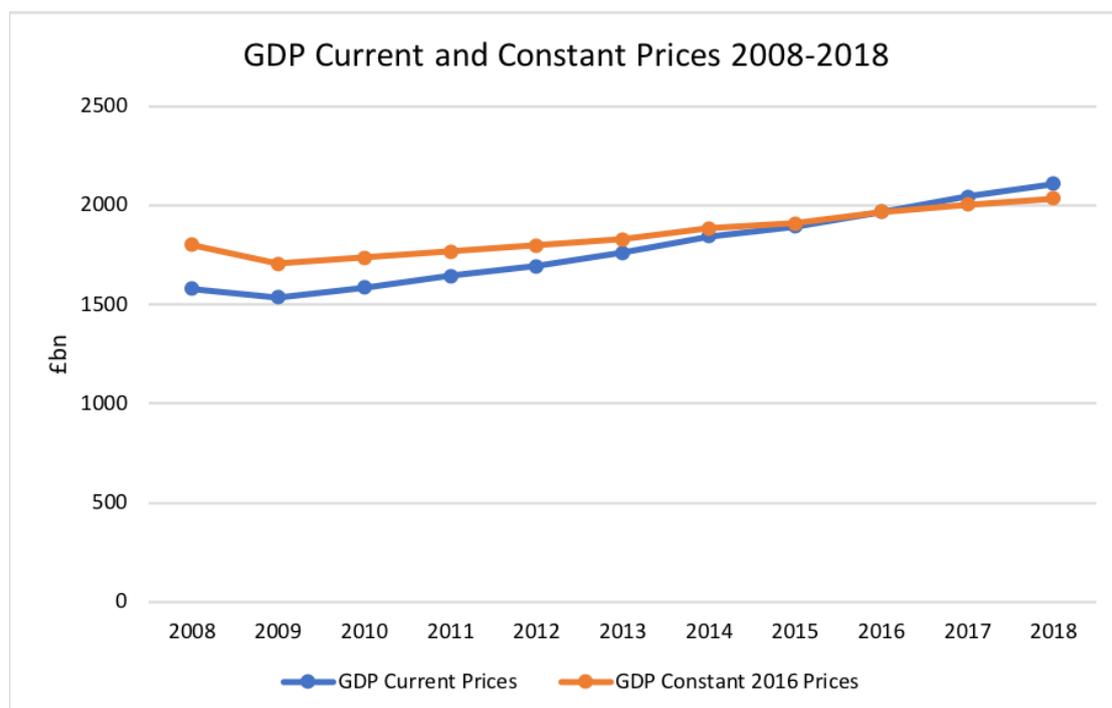
Figure 1: GDP in current and constant (2016) prices 2008-2018. Source: Office for National Statistics

In 2017, government expenditure (specifically Total Managed Expenditure) was approximately £770bn or around 40% of GDP. In 2008, expenditure was approximately £606bn and again around 40% of GDP. There have been fluctuations in this proportionality between government expenditure and GDP over time, but the figure is relatively stable. This implies that in real terms government expenditure has also grown over the period 2008-2018 by 13%.

Public sector accounts break down expenditure by broadly defined functions: Social protection; Health; Education; General public services; Economic Affairs and Defence. The constant price pattern of expenditure for these functions is depicted in Figure 2.
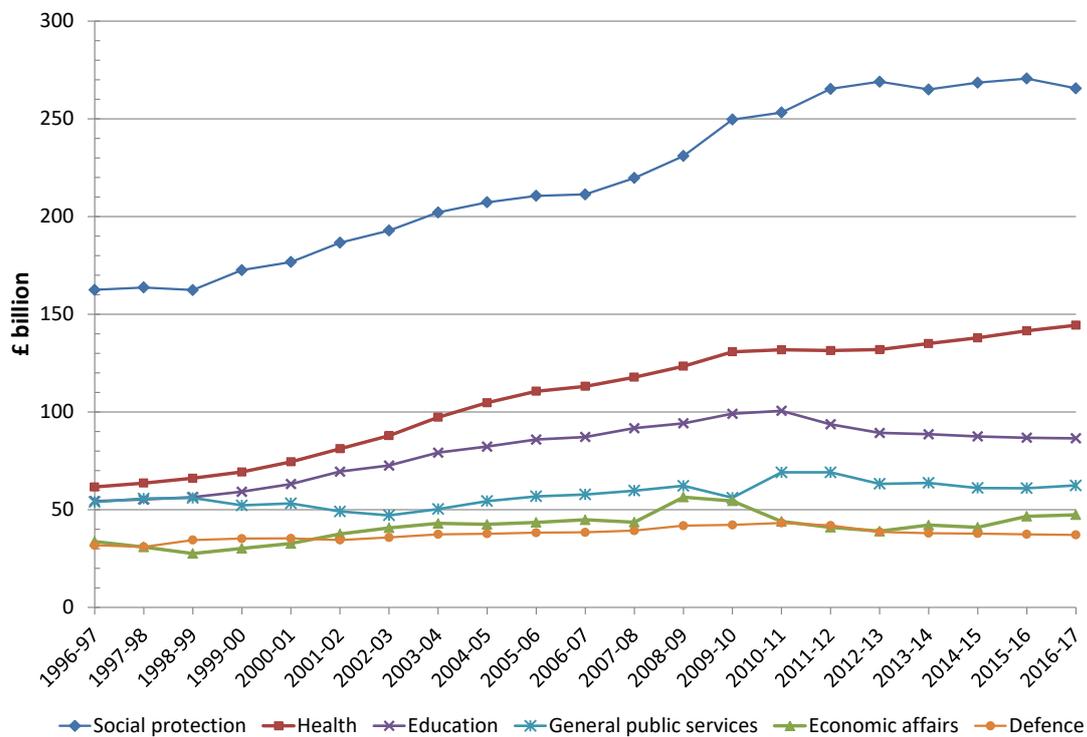
Figure 2: Public expenditure by function in constant prices 2008-2018.
Source: ONS Statistical Release February 2018

An upward sloping line indicates growth in real expenditure for that category. Health and social protection have shown a substantial real growth. For other categories, real expenditure has been almost flat over this period. The figures for overall growth in real expenditure from 2008 to 2018 are set out in Table 1.

Table 1: Growth in real public expenditure from 2008 to 2018 by category. Source: As in Figure 2.

Category	Growth in real expenditure 2008-2018
Social protection	23%
Health	25%
Education	-5%
General public services	5%
Economic affairs	10%
Defence	-6%

Hence expenditure on health has increased, in real terms, by substantially more than the underlying growth of the economy, and faster than every other category of government expenditure. This has happened at a time when public finances have been under pressure due to the financial crisis in 2008. This lends tentative support to an approach that focuses on expenditure as proxy of need, since there is no evidence, even at a time of economic austerity that health expenditure has been driven, on average, by economic circumstances. This is in contrast with other elements of public expenditure. However, the underlying drivers of HCE still need to be understood.

Methods

The study involves three work packages (WPs).

1. A literature review of drivers of past trends in health care expenditure (WP1).
2. Analysis of in-house database to quantify variations in health care expenditure across settings (WP2). We used three different measures to disentangle changes due to cost and changes due to volume.
3. Synthesis of findings from WP1 and WP2 to identify the key steps needed to move towards a projections model of health care expenditure (WP3).

WP1: Drivers of past trends in HCE

To identify known drivers of health care expenditure, we undertook a rapid literature review focussed on recent studies published since 2008. We searched three electronic databases. The strategy was written for Medline, then adapted for EMBASE and Econlit.

In total, 3454 records were identified after de-duplication. A further 25 relevant papers were identified by the team. Two team members (MJA, IRS) screened the hits using the following criteria:

1. Identifies drivers or predictors of demand for health care or long-term care.
2. Outcome variable is health care expenditure, or service utilisation.
3. The study employs statistical analysis or modelling (is not purely descriptive).
4. Study is not set in a lower- or middle-income country (LMIC).

The first 100 records were screened and any differences in opinion were discussed. Data were extracted (MJA, IRS, AM) using the following fields:

- Country setting.
- Data type.
- Methodology.
- Independent variable.
- Explanatory variable(s).
- Key results.
- Type of study (e.g. uses aggregated data, decomposition, methodological paper, literature review, projections).

For studies that used individual level data, we extracted additional information on the dependent variable:

- Time period (e.g. annual or monthly HCE).
- Care setting(s) (inpatient, primary care, etc.).

Studies were too heterogeneous to permit formal evidence synthesis: we could not quantify effects by pooling study findings. However, we describe the drivers, and their reported effects, by setting where possible.

A key aim was to identify lessons for development of a de novo model of healthcare demand, including whether drivers themselves or their relative impact varies by care setting.

WP2: Variation across settings in HCE

WP2 explored the suitability of our in-house longitudinal datasets (developed for calculating national productivity indices [14]) for describing trends in HCE by care setting, and quantifying their relative contributions to total spend. We used tables and graphs to illustrate variations, and distinguished between trends in activity and trends in costs.

The second research question was to quantify the relative contribution of the different healthcare settings to the overall HCE. We analysed expenditure trends for 17 settings for the 10-year period between 2008/09 and 2016/17. Three data sources were used: (i) National Schedule of Reference Costs (RC) (activity and costs); (ii) Prescription Cost Analysis (PCA) data[2] (quantity and costs) and (iii) Primary care consultation estimates[3] [15] based on the GP Patient Survey (GPPS) with costs sourced from PSSRU unit costs. Table 2 describes the healthcare settings analysed.

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[2] PCA data is supplied by the Prescription Pricing Authority via the NHS Digital Prescription Drugs Team.
[3] See Bojke et al. (2017) [15] for a full description of the method used to estimate consultation rates.

Table 2 Healthcare settings in the English NHS

Broad setting	All settings	Type of Activity	Years analysed	Activity Source	Cost Source
Hospital Based Care (HBC)	Inpatient Care	FCE and Excess bed days	2008/09 - 2016/17	RC	RC
	Outpatient	Attendances and procedures	2008/09 - 2016/17	RC	RC
	A&E	Attendances and activity	2008/09 - 2016/17	RC	RC
	Specialist Services	Activity	2008/09 - 2016/17	RC	RC
Diagnostics and Therapeutics (D&T)	Chemotherapy	Activity	2008/09 - 2016/17	RC	RC
	Radiotherapy	Activity	2008/09 - 2016/17	RC	RC
	High Cost Drugs	Activity	2008/09 - 2016/17	RC	RC
	Radiology	Examinations	2008/09 - 2016/17	RC	RC
	Diagnostic Tests	Tests	2008/09 - 2016/17	RC	RC
	Renal Dialysis	Sessions	2008/09 - 2016/17	RC	RC
Mental Health Services (MH)	Mental Health Services	Episodes, attendances and assessments	2011/12 - 2016/17	RC	RC
Primary Care (PC)	Primary Care	Consultations	2008/09 - 2016/17	Estimation using GPPS	PSSRU unit costs
Community Care (CC)	Community Prescribing	Prescriptions	2008/09 - 2016/17	PCA	PCA
	Community Care	Activity	2008/09 - 2016/17	RC	RC
	Optometry & Dentistry	Number of eye tests and dental procedures in Bands	2008/09 - 2016/18	NHS Digital	NHS Digital/ Ass. Optometrists
	Rehabilitation	Activity	2008/09 - 2016/17	RC	RC
Other (O)	Other*	Activity	2008/09 - 2016/17	RC	RC

FCE: Finished Consultant Episode; RC: Reference Costs; GPPS: GP Patient Survey; PSSRU: Personal Social Services Research Unit; PCA: Prescription Cost Analysis

*Regular Day and Night Admissions (RDNA), Audiology Services, Day Care Facilities and Hospital at home/Early discharge schemes. The classification of these activities has changed over time - see Castelli et al. 2018 for more information [14]

Changes in HCE may be driven by changes in activity and/or costs. To disentangle these, we computed three different measures: (i) Laspeyres Volume index, (ii) Paasche Price index and (iii) Total Expenditure growth.

Equation 1 Laspeyres Volume Index

$$X^L_{(0,t)} = \frac{\sum_{j=1}^{J} x_{jt} c_{j0}}{\sum_{j=1}^{J} x_{j0} c_{j0}}$$

Equation 2 Paasche Cost Index

$$C^P_{(0,t)} = \frac{\sum_{j=1}^{J} x_{jt} c_{jt}}{\sum_{j=1}^{J} x_{jt} c_{j0}}$$

Equation 3 Total Expenditure Growth

$$V_{(0,t)} = C^P_{(0,t)} * X^L_{(0,t)} = \frac{\sum_{j=1}^{J} x_{jt} c_{jt}}{\sum_{j=1}^{J} x_{j0} c_{j0}}$$

Where x_j represents the number of FCE/attendances/treatments of type j, where j=1…J; c_j indicates the cost of output *j* and *t* indicates time with 0 indicating the first period of the time series.

WP3: Next Steps towards a Projections Model

In this work package, we synthesised findings from WP1 and WP2 to identify the key steps needed to move towards a projections model of health care expenditure.

Results

In this section, we provide an overview of findings from the review of drivers of past trends in HCE (WP1). For setting-specific results, we report both review findings (WP1) and a quantitative analyses of how HCE trends vary across settings in England (WP2), using three different measures to disentangle changes due to cost and changes due to volume of activity.

We were unable to quantify the contribution of different drivers identified in the literature due to heterogeneity in their methods, but where possible we report relative contributions.

Drivers of past trends in HCE

The screening process identified 115 relevant papers (an overview is in Table 3). Our review focuses on findings from 54 of these articles [10, 16-68] that analysed individual-level data to identify factors driving HCE, expenditure on long-term care or health care utilisation. The remaining articles comprised six reviews [69-74], three methodological papers [75-77] and 52 macroeconomic studies using aggregate data [78-129].

Findings from reviews and aggregate studies of HCE

Research into the causes of rising health care expenditure began in 1977 with Newhouse's seminal study. Using data from 1970 for 13 OECD countries, Newhouse found that wealth explained 90% of the variation in HCE and estimated that the income elasticity of demand for health care services lay between 1.15 and 1.31, making healthcare a luxury good [71]. In the same decade, Grossman's human capital model was the first to consider drivers of demand from the 'consumer' perspective [95], postulating that the demand for health care is a derived demand for health with individuals using medical care and their own time to invest in and maintain or restore a depreciating human capital stock [90].

In the 1980s and 1990s, methods became more sophisticated as sample sizes increased, studies analysed multiple years of data rather than single years, and the biases and risks of spurious inferences implicit in time series analyses were better recognised [71]. Projection models using aggregate HCE data were based on a small number of explanatory variables such as income (per capita GDP) and prices [69]. There was increasing recognition that income could not fully explain observed rises in HCE relative to growth in GDP [90]. New estimates of the income elasticity of demand for health care usually placed its value at or below 1, making health care a normal good. However, findings were shown to be sensitive to the level of aggregation (e.g. national vs. regional) [40, 71], the model specification [112] and to the range of covariates included in the model [124]. In addition to testing the effect of national income on HCE, analyses considered factors such as population ageing and the share of total public expenditure [95]. The 'red herring' hypothesis, proposed in the late 1990s, held that time-to-death (TTD), rather than age, was the key demographic driver of HCE [130]. The validity of the red-herring hypothesis has subsequently been extensively explored and debated using both aggregate data [85, 98] and individual-level studies (see section below, Expenditure at the end-of-life).

In the 2000s, improvements in computing processing performance helped to popularise microsimulation models – examples include the Future Elderly Model in the US, and the Canadian Population Health Model (POHEM) [69]. These models simulate the behaviour and characteristics of different groups of individuals, defined by clinical condition, socio-economic status, or other demographic profile [69] and can be used to project the impact of changes in these characteristics on aggregate HCE. They are also used to explore 'what if' scenarios to inform potential policy reforms, for example, the impact of changes in behavioural and technological factors [69] or changes in prices [95, 120].

Table 3: Overview of studies from the literature review

Topic	Reviews / critique N=6	Methodological N=3	Aggregate data N=52	Individual level N=54
DRIVERS				
Behaviours			Grossman model [95]	Lifestyle factors [42]
End of Life care (EoL)			[85, 89, 98, 119]	[16, 17, 19, 20, 27, 34, 37-41, 44, 46, 50, 51]
Input prices/wages			[94, 95, 118, 120]	
Morbidity/disability/compression			[85]	Various morbidity indices [18, 22, 23, 25, 26, 30, 31, 54, 56, 67] and disability measures [27-29, 35, 36, 41, 46, 49, 52, 53, 60-64, 67, 68] Compression of morbidity/EoL [21, 29, 41, 44, 66]
Technology & Pharmaceuticals	Pharmaceuticals [73]	Theoretical models of demand and supply to develop typology of new technologies [75]	Technology [90, 108, 123, 124, 127] Pharmaceuticals [105, 114, 115]	Pharmaceuticals [21, 28, 30, 40, 43, 50, 63]. Technology [21, 28, 40]
MODELLING APPROACH				
Comparison of models	Comparison of 25 micro, component-based and macro models for forecasting HCE [69]		[94, 117, 118, 123, 127]	[18, 22, 26, 30, 43]
Cost distribution				Use of quantile or multinomial regression, high users [24, 35, 53, 55, 58, 59, 68]
Decomposition			[92, 102, 112, 125, 129]	[28, 33, 57, 64]
Projections models (non-US)			[79, 85, 102, 104, 107, 122]	[21, 29, 60]
Simulations	Microsimulation models [69]	Human-capital based endogenous growth model [76] Microsimulation models [77]	[80, 81, 84]	[23, 45, 48, 49, 62, 63, 65, 66]

Topic	Reviews / critique N=6	Methodological N=3	Aggregate data N=52	Individual level N=54
COUNTRY SETTING				
Cross-country comparisons	Factors driving HCE in OECD countries [71]		[78, 83, 90, 95, 96, 111, 113, 120, 121, 124, 128]	[61]
single country excl. US			[82, 86, 91, 97, 106, 109, 117, 126]	[10, 17, 19-23, 25, 27-29, 32, 34, 37-42, 44, 47-51, 53, 54, 57-59, 62-68]
US only	Drivers (technology etc.) of US healthcare costs [70]		US projections model [87, 88, 93, 99-101, 116] Analysis of state variations [86], technology [108]	[16, 18, 24, 26, 30, 31, 33, 35, 36, 43, 45, 46, 52, 55, 56, 60]

More recently, macro-level studies of US expenditure have identified strong positive relationships between HCE and technological progress [71, 108]. A study of 16 OECD countries, including the US, used time trends as a proxy for technology and concluded that models that fail to control for technological progress will overestimate the income elasticity of demand [124]. A decomposition analysis of 18 OECD countries used a measure of approved medical devices and drugs to proxy technological development. On average, technology explained 37% of historical HCE growth (ranging from 19% to 56%, with the UK at 27%) [123]. Others have argued that the effect of technological advances on HCE partly depends on the price elasticity of demand for health care but, counterintuitively, that uptake of Health Technology Assessment is associated with higher levels of HCE [90]. This could be a case of 'reverse causality': countries where technological advances are perceived to be a major and persistent driver of HCE are more likely to adopt HTA systems in an attempt to manage the uptake of new high cost drugs and devices.

Two of the aggregate studies assessed prevention. In their analysis of 18 OECD countries, Willeme and Dumont (2015) tested the population 'average' body mass index (BMI) to capture lifestyle factors as a structural determinant of HCE. BMI explained on average 20% of historical growth in total HCE (range: 12% to 32%; UK: 27%) [123]. In an Australian simulation study, Cadilhac et al (2011) modelled the costs and benefits of reducing six risk factors.[4] Expected reductions in risk factors were based on expert consensus. The authors estimated cost savings of around 2% of total annual HCE, and a reduction in Disability Adjusted Life Years of 3.6% over the cohort lifetime [81].

Findings from studies that used individual-level data

The studies using individual-level data identified in our search most often rely on observational, non-experimental data from administrative databases, such as claims data or registers, or on survey data or cohort studies. We identified 54 studies using individual data. Most were from the US (30%), the UK (15%) or the rest of the EU (35%). Five were from Australia or New Zealand (9%), one study was from China and two were from Japan. The remaining studies were from Canada, Norway and Switzerland. We excluded lower and middle-income countries (LMICs) from the review.

The studies analysed drivers of expenditure from a range of care settings (Table 4) and adjusted for different sets of covariates (Table 5). The care settings are those captured by the dependent variable, i.e. the measure of expenditure. In this section, we describe groups of studies categorised broadly according to their main outcome: studies analysing health care expenditure (N=40), long-term care expenditure (N=4), cost of illness (N=4), service use (N=5) and health outcomes (N=1). In the subsequent section, we summarise findings by setting (where available).

Studies analysing health care expenditure

In most studies in our review (40/54, 74%), **health care expenditure** was the dependent variable. This group of studies excluded those that evaluated expenditure on particular diagnoses such as dementia or cancer (we describe cost of illness studies below). Most of the HCE studies (24/40, 62%) calculated expenditure from multiple care settings though seldom reported drivers separately by setting; exceptions were de Meijer 2013[5] [28], Hakkinen 2008 [40][6] and Deb and Norton 2018 [26][7]. Most studies explicitly included the cost of hospital inpatient care (29/40; 73%), but study authors did not always explain how total expenditure had been constructed [34, 43, 68].

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[4] Tobacco smoking; inadequate fruit and vegetable consumption; high risk alcohol consumption; high body mass index; physical inactivity; and intimate partner violence.
[5] Separate analyses for inpatient expenditure and community pharmaceutical expenditure.
[6] Separate analyses for non-psychiatric specialist care, psychiatric inpatient care, long-term care and prescribed medicines.
[7] Separate analyses for A&E attendance and primary care (office-based visits).

Just one study assessed lifetime costs [23], with remaining studies measuring expenditure over 12 months or less, e.g. quarterly [37], monthly [27] or daily expenditure [59].

In terms of explanatory variables (Table 5), HCE studies all controlled for age and sex, two-thirds included comorbidities and fewer than half of the studies included time-to-death (TTD) or socio-economic status as explanatory variables.

However, it is not possible to make general inferences about the drivers of demand based on this group of studies. Findings were diverse and the studies differed in their research questions in terms of care setting(s), demographic or population group studied, methodology and the set of explanatory variables (both those of primary interest and controls). The motivation for the studies was also very variable, ranging from the assessment of alternative model specifications [22, 30, 43] to addressing practical challenges in setting budgets [10, 47]. Where available, setting-specific findings from these studies are reported below.

Studies analysing long-term care expenditure

Four studies investigated predictors of expenditure on **long-term care (LTC)** [27, 29, 49, 53], i.e. spend on home care and/or institutional care. These studies all adjusted for age, gender, and disabilities, and three studies also controlled for socio-economic status.

A Dutch study of publicly funded LTC expenditures (LTCE) by de Meijer and colleagues (2011) adjusted for a range of variables including time-to-death (TTD), cause of death and co-residence status [27]. The authors used two-part models, considering institutional and homecare LTC separately and in combination. An important conclusion was that TTD is a proxy for disability when analysing homecare expenditure.[8] Whereas TTD can only be known retrospectively, disability can be measured in real-time. Therefore, disability prevalence and incidence are potentially useful inputs for projection models of LTCE, provided disability measures are sufficiently standardised. The authors note there is scope for improvement in this regard.

Regarding the impact of diseases (causes of death) on LTC spend, de Meijer et al. (2011) found this was variable: for example, cancer deaths were associated with lower LTC spend, whereas spend was higher for deaths due to diabetes, mental illness, stroke, respiratory illness or gastrointestinal disease [27]. Living alone was also associated with higher LTCE, driven by higher use of institutional care (as opposed to home care). Men were less likely than women to utilise LTC, and had lower expenditures for both institutional and home care. Although the inclusion of TTD in the model attenuated the effect of age on both types of LTCE, the effect remained statistically significant [27].

In a subsequent paper, de Meijer et al. (2012) [29] explored the impact of changing disability trends on both individual lifetime LTC spend and on population aggregate spend. The impact of improved life expectancy on spend was found to depend on the proportion of years spent in severe disability, since this was the principal driver for utilisation of institutional care. Therefore, policies that 'stimulate' a compression of disability are an important way of controlling lifetime LTC spend, although aggregate spending may still rise if the population continues to age [29]. Malley and colleagues (2011) concur with the importance of life-expectancy (LE) as a driver of LTC expenditure [49], but emphasise the high level of uncertainty about future trends in LE and hence its impacts.

Olivares-Tirado et al. (2011) concluded that the introduction of the Japanese universal LTC insurance system was, in part, responsible for rises in LTC spend but noted that other evaluations had ruled

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[8] Predictions for institutional care spend were not feasible due to a lack of data on disability.

out supplier-induced demand as a cause [53]. In this case, it appeared that the insurance system facilitated access to institutional care for people with high (and hitherto unmet) care needs.

One of the HCE studies [40] also investigated LTC utilisation and spend. Confirming findings by de Meijer et al. (2011) [27], Hakkinen et al. (2008) showed that females were more likely to use LTC and the likelihood rose with age even after controlling for death (survival) [40]. Annual LTCE was approximately 7-11% higher in women. Unsurprisingly, shorter TTD was related to a higher probability of LTC utilisation [40].

Studies analysing cost-of-illness

Measuring morbidity and apportioning costs reliably are important when projecting future HCE. This is particularly so if their prevalence grows at different rates. For example, in diseases where genetics are the main risk factor prevalence may be stable, whereas the prevalence of conditions linked to lifestyle behaviours or that are age-related may be more volatile.

Cost-of-illness studies covered migraine [18], Alzheimer's disease [45], 10 non-communicable diseases [25], [9] and 154 causes of illness [31]. All four studies tested the impact of age on health care cost and adjusted for comorbidities.

Baser et al. (2008) used US claims data to investigate the impact of comorbidity on the total annual costs for people with migraine [18]. The authors tested all possible permutations of three commonly used morbidity indices. The indices captured different risks (correlation was low), and the best predictive value was obtained when the three indices were modelled jointly. When composite scores for each comorbidity index were used, the estimated impact on expenditure was qualitatively similar to the impact when their individual components were modelled separately.

Cortaredona and Ventelou (2017) used data from a French National Health Insurance database to estimate the added impact of comorbidities on the costs of 10 non-communicable diseases [25]. They identified cases where costs were 'super-additive'; these arise when the sum of the costs of two comorbid conditions is greater than the sum of the costs of the two diseases in the absence of comorbidity. Evidence of super-additive costs was found for 41 of the 45 pairwise combinations of these 10 conditions. The authors concluded that prevention of an individual disease may reduce costs by more than the cost of the illness (cost x number of cases) would suggest. The study did not consider the impact of multi-morbidity involving three or more conditions.

Ignoring the impact of comorbidities on the cost of illness can over- or understate the true cost of illness. To generate more accurate disease-specific spending estimates, Dieleman et al. (2017) [31] undertook a 'comprehensive approach' using US inpatient data. They selected 154 chronic and acute conditions as primary diagnoses, then modelled the excess risk of spending due to each condition as a comorbidity. They calculated the attributable fraction of spend for each comorbidity and derived 'adjustment scalars' – these captured positive and negative changes in cost (resource flows) depending on whether the disease was the primary diagnosis (outflow) or a comorbidity (inflow). The comorbidity-adjusted spend was calculated as the sum of total expenditure on the condition, plus the 'net flow' (i.e. inflows *less* outflows). Around two-thirds of the 154 conditions had resources reallocated to or from the condition, with the redistribution ranging from +74% for chronic kidney disease to -21% for lower respiratory infections. The size of the impact varied by age.

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[9] Heart disease, stroke, diabetes, cancers (8 types), respiratory disease, major depression, alcohol-related diseases, cirrhosis, chronic kidney disease and chronic neurological disorders.

Hurd et al. (2015) [45] produced projections of the future costs of dementia care under alternative prevalence scenarios, both for dementia and for comorbidities associated with an increased risk of developing dementia (i.e. hypertension, obesity, diabetes – all of which are expected to become more prevalent). Unsurprisingly, declining prevalence of dementia was linked to lower rates of increase in projected aggregate spend and in the projected costs of informal care. By comparison, the impact of changes in comorbidity prevalence on cost estimates was small.

Table 4: Overview of studies: time period and settings covered by the dependent variable

Dependent Variable	No. Papers	Time Period			Settings									
		< 1 Year	Annual	> 1 Year	Hospital/ Inpatient/ Acute	Primary Care	Outpatient/ Specialist	Drugs	Medical Procedures	Tests	Devices/ Equipment	Emergency	LTC	Other*
Expenditure	40	8	31	1	29	17	17	22	2	7	4	8	5	17
LTC	4	1	2	1	0	0	0	0	0	0	0	0	4	0
Cost Specific Illness	4	0	4	0	4	1	3	3	1	1	1	1	1	0
Service Use	5	0	5	0	4	1	3	2	0	0	0	1	1	0
Health Outcome	1	0	1	0	1	1	0	1	0	0	0	0	0	0
Total	**54**				**38**	**20**	**23**	**28**	**3**	**8**	**5**	**10**	**11**	**17**

* 'Other' includes informal care, out of pocket costs, dental, rehabilitation

Table 5: Overview of studies: explanatory variables

Dependent Variable	Number of Papers	Explanatory Variables													
		Age	Sex / gender	Proximity to Death / Life Expectancy	Diagnoses / Comorbidities	Disability	Healthy / Risky Behaviours	Deprivation / Income / Education	Insurance	Service Use	Health Status	Supply	Region	Other *
Expenditure	40	40	40	16	27	10	5	18	12	6	11	4	9	24
LTC	4	4	4	3	2	4	0	3	0	1	0	1	0	3
Cost Specific Illness	4	4	2	0	4	0	1	1	1	0	1	0	1	2
Service Use	5	5	4	1	5	3	1	3	2	2	2	0	0	1
Health Outcome	1	1	1	0	1	0	1	0	0	0	0	0	0	0
Total	**54**	**54**	**51**	**20**	**39**	**17**	**8**	**25**	**15**	**9**	**14**	**5**	**10**	**30**

* 'Other' includes ethnicity, cause of death, residential status.

Studies analysing service use

Five studies focused on factors driving **service utilisation**, all of which controlled for age and for comorbidities [32, 36, 42, 52, 61]. There was no evidence from the UK. The two US studies [36, 52] compared models for both utilisation and expenditure.[10]

A descriptive analysis of rising trends in A&E attendances in Australia [32] showed that presentation rates were highest in the youngest and oldest age groups (U shaped curve), but rose in all age groups between 2010 and 2014.

In a paper investigating methodological extensions to the two-part model for predicting individual or aggregate annual healthcare spend in the US, Frees et al. (2011) identified drivers of inpatient and outpatient hospital utilisation [36]. The principal-agent theory underpins the two-part model: individuals (principals) make the initial decision to seek care (i.e. utilisation occurs); then the clinician (agent) mainly determines the scope and intensity of that care (and so its cost). The authors extended this framework by modelling the number of events within a year, and then linked expenditure to the frequency of events. This helped them distinguish factors affecting 'demand' (the decision(s) to seek care) from those driving subsequent expenditure. Age and insurance status were the only factors driving both utilisation and expenditure. In general, drivers of utilisation – socioeconomic status, health status and having a 'usual' source of care – did not significantly explain annual expenditure on either inpatient or outpatient care [36].

Mukherji et al. (2016) tested a range of methods for modelling two measures of healthcare demand: hospital stays and out-of-pocket expenditure [52]. The two outcomes were modelled jointly, taking account of their correlation. The models also allowed for non-linear effects of age, and interacted age and gender. The authors confirmed findings by Frees (2011) [36] that determinants of the probability of hospital utilisation do not necessarily explain frequency of use [52]. Factors significant in explaining hospital utilisation – such as self-reported health – were not necessarily predictive of out-of-pocket expenditure. The authors found notable gender differences in the propensity to use inpatient services and to incur out-of-pocket expenses, with differences also varying by age.

Sirven and Rapp (2017) used dynamic panel models to investigate factors affecting hospital admission in older people in Europe [61]. These models take account of 'state dependence', or persistence in use, in the outcome variable (hospital use) over time. The authors also included lagged variables of other types of care (visits to GPs and to specialists), as these are potential complements to or substitutes for hospital care in the same period. Frailty was found to be a key driver of hospitalisation, whereas previous specialist visits were negatively associated with hospitalisation, suggesting they may have a preventative effect.

Hernández-Aceituno et al. (2017) [42] considered the impact of clusters of "healthy" behaviours on health service use. The study of 2000 older Spanish individuals tested the impact of six self-reported behaviours [11] at baseline on subsequent healthcare use (duration of follow up varied across the sample). Those reporting four or more healthy behaviours at baseline had a lower risk of polypharmacy and hospitalisation [42]. The impact on primary care visits depended on whether the analysis controlled for other factors, such as comorbidity; visits to a medical specialist were not linked to healthy behaviours.

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[10] The review included other two-part models, but as our focus was on drivers of HCE we do not review the 'utilisation' component of these studies here.

[11] Smoking, physical activity, diet, sleeping, sedentary behaviour, cohabitation.

Studies analysing health outcomes

The Australian study of **health outcomes** [48] by Lymer and colleagues (2016) described the simulation model 'NCDMod' for chronic disease. The model used static and dynamic methods to capture the effects of population ageing on disease burden. As the model included health system expenditure, both the effects and cost-effectiveness of preventative and disease-modifying interventions could be explored. It could also be linked to a separate model (Health&WealthMOD2030) to generate projections of long-term costs [48], though few details were reported in the paper.

Setting-specific results

In this section, we draw together data from the analysis of trends in NHS expenditure and findings from the literature. Figure 3 shows how total growth in expenditure varied by care setting, with 2008/09 as the base year (100). Chemotherapy and high cost drugs exhibit the largest rates of growth. These growth rates were driven mainly by increases in the volume of activity. Table 6 provides an overview of the expenditure growth rates by setting.

Full details of the analysis of trends are in the **spreadsheet accompanying this report**.

Table 6: Growth rates in expenditure, volume and cost by setting: England, 2008/09 to 2016/17

		Total Growth 08/09-16/17				Mean year-on-year growth		
	All settings	Expenditure	Volume	Cost		Expenditure	Volume	Cost
Hospital Based Care (HBC)	Inpatient Care	38.6%	19.5%	16.0%		4.2%	2.3%	1.9%
	Outpatient	57.2%	43.7%	9.4%		5.8%	4.7%	1.1%
	A&E	59.5%	30.2%	22.5%		6.0%	3.4%	2.6%
	Specialist Services	34.8%	21.7%	10.8%		3.8%	2.5%	1.3%
Diagnostics and Therapeutics (D&T)	Chemotherapy	113.1%	110.2%	1.4%		10.0%	9.9%	0.4%
	Radiotherapy	42.9%	72.1%	-17.0%		4.6%	7.3%	-2.2%
	High Cost Drugs	230.7%	270.5%	-10.7%		16.7%	18.0%	-1.2%
	Radiology	34.1%	39.8%	-4.1%		3.8%	4.3%	-0.5%
	Diagnostic Tests	47.3%	59.0%	-7.4%		5.1%	6.2%	-0.8%
	Renal Dialysis	16.1%	-1.0%	-1.0%		1.9%	-0.1%	2.0%
Mental Health Services (MH)	Mental Health 2011/12 - 2016/17	5.5%	8.6%	-2.8%		1.2%	1.7%	-0.5%
Primary Care (PC)	Primary Care	NA	NA	NA		1.5%	0.4%	1.0%
Community Care (CC)	Community Prescribing	9.8%	45.2%	-24.4%		1.2%	4.8%	-3.4%
	Community Care	35.0%	18.7%	13.8%		4.0%	2.4%	1.6%
	Optometry & Dentistry	23.7%	7.2%	15.3%		2.7%	0.9%	1.8%
	Rehabilitation	10.4%	-2.3%	13.1%		1.5%	-0.1%	1.6%
Other (O)	Other*	-13.9%	-14.1%	0.2%		-1.7%	-1.7%	0.1%

*Regular Day and Night Admissions (RDNA), Audiology Services, Day Care Facilities and Hospital at home/ Early discharge schemes. The classification of these activities has changed over time [14].
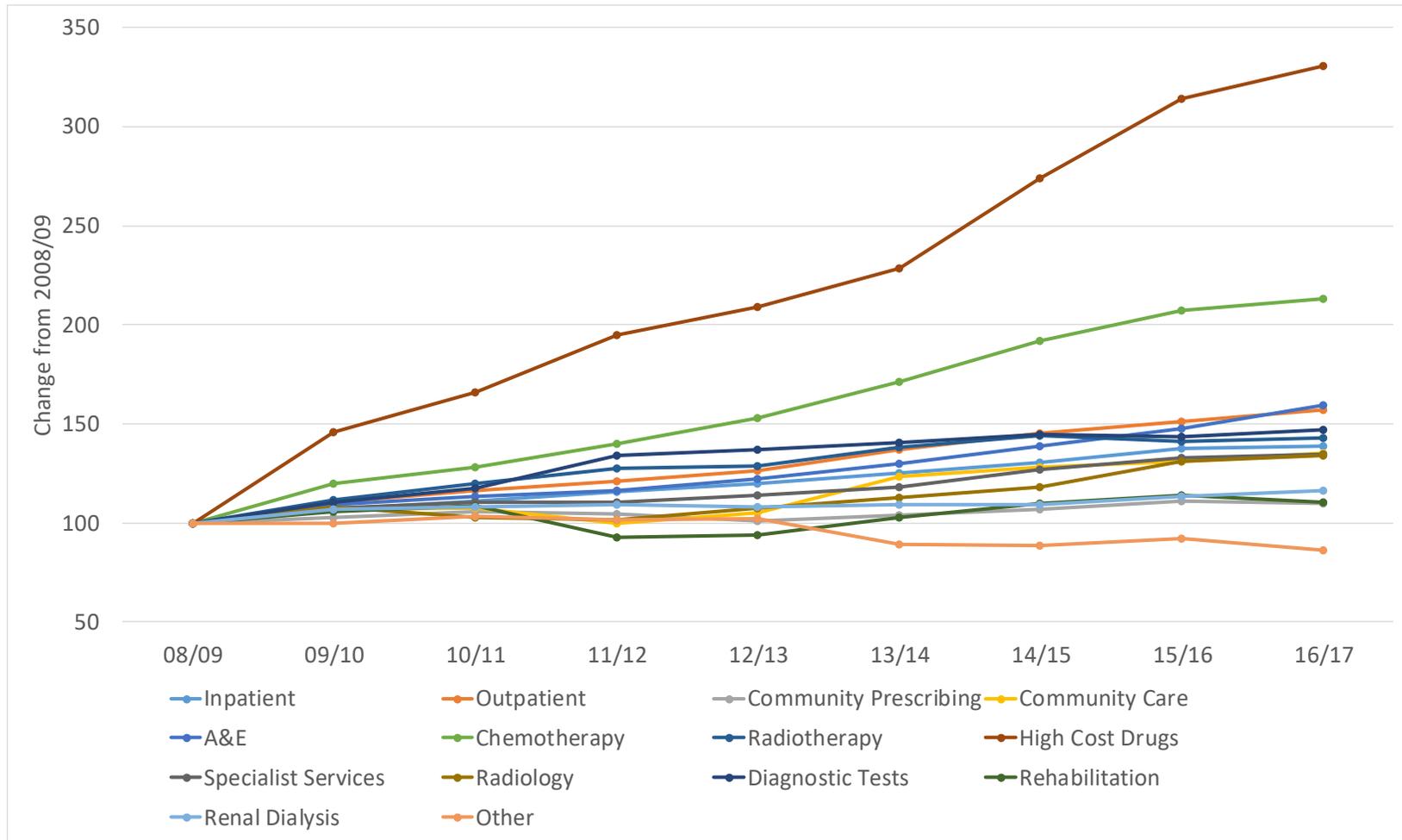
Figure 3: Total growth in current expenditure: all settings

Note: Excludes Primary Care and Mental Health Services trends. These are in the accompanying spreadsheet: Trends by setting report version_20190301.xlsx. Primary care has a break in the series and Mental Health Services starting point is later than 08/09.

Hospital-based care

This includes inpatient, outpatient, A&E and specialist services.

Inpatient Care

Trends in inpatient expenditure

Inpatient care is the largest setting in the NHS and accounted for 31.5% of the total NHS expenditure in 2016/17. Inpatient care comprises three broad categories: elective, day cases and non-elective activity. The smooth growth of the total expenditure masks large variations that occur at the sub-setting level. Activity and expenditure on short-stay non-electives and elective day cases increased substantially over the study period.

From 2008/9 to 2016/17:
- **total inpatient** expenditure rose by 39% in total, equating to a mean annual rise of 4.2%
- total inpatient volume rose by 2.3% annually; for costs, the corresponding figure was 1.9%
- trends in **elective care** reflect a switch towards day cases, possibly due to Best Practice Tariff incentives
  - elective care comprises inpatient cases and day cases
  - on average, expenditure on elective care grew by 1.3% annually, driven by rises in cost (2.0%)
  - elective inpatient activity declined, with a mean annual growth rate of -0.6%
  - for day cases, the mean annual growth rates in expenditure, activity and costs were 5.2%, 3.8% and 1.3% respectively
- **non-elective care** grew more rapidly than the other sub-settings
  - expenditure grew by 7.2% for short-stay care and 4.9% for long-stay care
  - volume grew by 4.9% for short-stay care and 3.0% for long-stay care
  - costs rose 2.2% for short-stay care and 1.9% for long-stay care

Findings from the literature review – inpatient expenditure

Although most studies include inpatient care within their measure of HCE, only a subset reported drivers separately for this care setting [28, 37-39, 44, 52, 57, 59, 61, 65, 67]. Our review identified only one study that distinguished the effects of changes in elective and non-elective care [57].

Decomposition of HCE

Most studies implicitly assume the relationship between HCE and its drivers is stable over time. However, two studies explored the implications of relaxing this assumption [28, 57]. Although based on data from different countries, findings were consistent across the studies: changes in expenditure were mainly explained by changes in the value of the drivers rather than by changes in the relationship between the drivers and HCE. The key driver was changes in care settings, with both studies finding changes in demographic factors to be negligible.

One study that investigated changes in the relationship between HCE and its drivers over time was from England [57]. This was the only study we reviewed that separately reported the effects of changes in elective and non-elective inpatient activity. Using a 1% random sample from HES,[12] Rice and Aragón (2018) analysed how the total annual cost of hospital inpatient services varied between the years 2007/08 and 2014/15 [57]. They decomposed these variations into those due to changes in the mean value of the characteristics of the sample (e.g. population age) and those due to changes

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[12] HES: Hospital Episode Statistics, https://digital.nhs.uk/data-and-information/data-tools-and-services/data-services/hospital-episode-statistics [accessed 21 March 2019].

in the relationship between these characteristics and expenditure (e.g. the coefficient on the age variable). They included the type of activity, elective and non-elective, as explanatory variables along with demographic characteristics, diagnoses and treatments, and type of provider.

Across the two periods, the (geometric[13]) mean patient expenditure rose by 7.2% (21.6% in real terms), which decomposed into a change in the characteristics (8.9%), changes in the relationship between characteristics and expenditure (-0.7%), and the interaction between these two effects (-0.9%). These statistics relate to the overall changes (across all covariates), and mask considerable variation in the size and direction of effects for individual covariates. Changes in the composition of activity contributed to the overall increase in cost through two mechanisms: first, changes in the number of elective/non-elective episodes (changes in means of the characteristics in each period); and second, via changes in the relationship between episodes and cost (changes in the coefficients) [57]. The effect of changes in the demographic factors – age and sex – was 'negligible' in determining changes in expenditure across the periods, whereas the increase in prevalence of morbidities had a comparatively large impact on costs.

The second decomposition study was from the Netherlands. In 2001, fixed global hospital budgets in the Netherlands were relaxed in response to prolonged waiting times, presenting an opportunity to trace how additional funding was distributed across different types of patient and setting. De Meijer and colleagues (2013) [28] analysed linked data on individuals with sickness fund insurance to investigate how drivers of HCE vary across the distribution of expenditure. They partitioned the observed change in the distribution of HCE into changes in the drivers (determinants), and 'structural' changes in the relationship between the drivers and HCE – these may be caused by changes in regulation, policy or technology. Hospital expenditure comprised inpatient care (including inpatient medication), outpatient care and rehabilitation. The authors did not distinguish between elective and emergency admissions.

Over the study period (1998-2004), mean hospital expenditure rose by 18%. Using decomposition analysis, de Meijer and colleagues showed that the increase throughout most the distribution was driven by changes in drivers, partly offset by a much smaller negative effect of structural shifts [28]. The largest increase was at the centre of the distribution. An investigation of individual drivers revealed a move away from inpatient care and a higher rate of day case admissions, shorter inpatient stays and greater use of outpatient clinics. Changes in the age/sex distribution and in disease burden[14] had no discernible effect in explaining the rise in hospital expenditure; the impact of hospital procedures was mixed. The negative effect of structural changes was larger in individuals with positive hospital expenditures (compared with the study sample as a whole). However, structural changes actually increased costs for those in the top quintile of HCE, which, the authors speculate, could be due to greater use of new technologies.

Studies exploring other dynamics in inpatient expenditures
Sirven and Rapp (2017) [61] used SHARE[15] data from 10 countries to understand persistence in the dynamics of hospital utilisation in people aged 50+. They found evidence of state dependence over time, and an association between frailty and hospitalization risk. Previous specialist practitioner visits were associated with lower risk of future hospitalization, suggesting a potential substitution effect.

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[13] The geometric mean indicates the central tendency by calculating the nth root of the product of n numbers. This differs from the arithmetic mean, which calculates the average of a sum of n numbers. Another way of expressing the geometric mean is the exponential of the arithmetic mean of the logarithm of the n numbers. Unless all numbers are equivalent, in which case the two means coincide, the geometric mean is always less than the arithmetic mean.

[14] Measured by two indicators: the prevalence of work-related disability payments and cause of death.

[15] Survey of Health, Ageing and Retirement in Europe

Gregersen (2014) [39] analysed Norwegian hospital admissions data and found that per capita HCE grew faster for older people (50+) compared with the rest of the population,[16] i.e. steepened over time. However, results were sensitive to model specification. Mortality-related expenditures also increased over time, and were identified as a driver of the observed 'steepening' effect.

Effects of baseline health on inpatient expenditures

Two studies examined the long-term effects of individuals' baseline health status on subsequent HCE [38, 67]. In their Scottish study of end of life (EoL) expenditure, Geue and colleagues (2015) found the effects of baseline health status were small, mixed and some appeared counterintuitive [38]. For example, smokers were at higher risk of hospital utilisation, but also had lower EoL costs on average than non-smokers. Baseline BMI and physical activity did not predict costs at the end of life [38]. Wouterse and colleagues (2011) [67] used Dutch data to investigate the relationship between baseline health and hospital costs. They found substantial and persistent differences in hospital costs between people aged 50 to 70 with good or bad baseline health. In the older age groups, expected hospital costs for those in bad health declined rapidly and, due to the higher mortality rate, fell below levels of those in good (baseline) health. The authors stress the importance of taking account of the interaction between health status and mortality when projecting costs, and caution against overreliance on better health to contain future HCE.

Expenditure at the end-of-life

Five studies investigated inpatient expenditures at the end of life (EoL) [37, 38, 44, 59, 65]. Geue and colleagues (2014, 2015) used Scottish data to show that both time to death (TTD) and age at death significantly predicted costs in the last 12 quarters of life [37, 38]. Interactions between age and TTD were also significant in predicting the probability of being hospitalised, with larger effects in younger age groups. The effects on HCE were similar but less pronounced [38]. The projected rate of growth in HCE was driven by factors such as TTD, increasing longevity and the postponement of diseases into older ages [37].

Wong and colleagues (2011) tested the effect of TTD on HCE using Dutch data, running separate two-part models for 94 diseases [65]. TTD had a positive effect on health care expenditures for most diseases and the effect was strongest for most cancers (especially lung and ovarian cancer). TTD was not a good predictor of spend on some nonlife threatening conditions, including chronic conditions and diseases treated with elective inpatient care. The effect of age was modest in comparison to TTD, although there was a lot of variation across different diseases.

Howdon and Rice (2018) [44] constructed a panel of individual inpatient health care users over a seven-year period directly preceding death to explore the determinants of expenditures, paying particular attention to the role played by age, TTD, and morbidity. English administrative data were used to link individuals over time and instrumental variable methods were employed to overcome the joint determination of health care expenditure and TTD. TTD dominated age as a key driver of health care expenditure, and morbidity characteristics dominated TTD. The finding that measures of morbidity are able to predict expenditure in the run-up to death more strongly than TTD was then located within the literature on the prospective prediction of hospital utilisation to inform resource allocation. This finding is particularly relevant to approaches that rely on individual-level data and which incorporate information on morbidity characteristics

Sato and colleagues (2009) analysed Japanese survey data on hospital utilisation, distinguishing users into low, medium and high HCE groups [59] and conducting a subgroup analysis of decedents in their last month of life. In the main analysis, death was associated with higher per capita daily

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[16] Excluding newborns, whose expenditures are increasing at a faster rate than the rest of the younger population.

HCE. HCE was also higher in younger decedents (40 to 64) compared with those aged 75+. The subgroup analysis of HCE in decedents found that use of diagnostic imaging, medical examination, treatment and surgery[17] were predictive of higher daily costs.

Studies of service utilisation

Mukherji et al. (2016) used a two-part mixture model to explain inpatient stays in older Americans [52]. The probability of (any) utilisation was higher in females, those with functional limitations, a higher BMI and in people who had experienced a recent change in self-reported health – but the presence of chronic conditions did not predict utilisation. In people who had a hospitalisation, the level of use was higher in those with chronic conditions, or with a change in self-assessed health, or in people with functional limitations. Gender and BMI were not associated with higher levels of use.

Outpatient

Trends in outpatient expenditure

Outpatient care is one of the largest settings in the NHS and accounted for 12.6% of total NHS expenditure in 2016/17. Activity in the outpatient setting can be classified in three major groups: consultant led activity, non-consultant led activity and procedures. The majority of expenditure is from Trusts, with other providers contributing data only up to 2011/12. We therefore focus on Trust values.

From 2008/09 to 2016/17:

- **total expenditure** increased by 57%
    o on average, 5.8% annually
    o annual growth ranged from 4.0% (2015/16 to 2016/17) to 10.7% (2008/09 to 2019/10)
- **volume** increased by 32% in total
    o on average, 4.7% annually
    o annual growth ranged from 2.0% (2011/12 to 2012/13) to 8.9% (2008/09 to 2019/10)
- **costs** increased by 10% in total
    o on average, 1.2% annually
    o only one year of negative growth (-0.9%) between 2010/11 and 2011/12

The figures for all providers differed slightly, with growth declining by 4% in 2010/11 and 2011/12. This may reflect a failure to capture data previously reported by PCTs. Bojke et al., 2014 [131] used an alternative data set for outpatient activity (the Outpatient Minimum Data set), and calculated that activity grew by 2.2% between 2010/11 and 2011/12.

Findings from the literature review – outpatient expenditure

We identified two studies analysing drivers of outpatient care utilisation or expenditure [21, 36], neither of which was from the UK.

Frees et al. (2011) tested several alternative models to identify factors associated with outpatient visits (utilisation and expenditure) in the US [36]. The number of visits was higher in older people, in females, and in those with college education or higher incomes. Utilisation was lower in people of Asian and Black ethnicity (compared to White ethnicity), but higher in people self-reporting being unemployed. Poorer self-rated physical or mental health, or other functional limitation, were

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[17] Treatments (medication, surgery etc.) were captured by dummy variables so do not assess the level of utilisation.

predictive of higher OP use. Having insurance or receiving managed care (enrolled in a gatekeeper plan) were also associated with higher use. In the expenditure analyses, findings were more mixed and inconsistent across models. In all models, older age, having insurance, having poorer self-assessed physical health or functional limitations were consistently associated with higher outpatient expenditure. None of the other factors, including managed care, gender, ethnicity, mental health and unemployment, was consistently associated with outpatient expenditure [36].

A Spanish study by Blanco-Moreno et al. (2013) reported that outpatient expenditure rose by 50% in real terms from 1998 to 2008 (similar to our analysis of trends in NHS Reference Costs). The percentage increase was highest in those of working age (63%) and in older people (58%) [21]. Although the overall aim of the study was to project public expenditure to 2060, drivers relating to setting-specific expenditure were not investigated.

A&E

Trends in A&E expenditure

This setting represented 5.7% of total NHS expenditure in 2016/17. It comprises activity performed in Emergency Departments and other A&E services (e.g. ophthalmology, dental, NHS walk in centres).

From 2008/09 to 2016/17:

- **total expenditure** increased by 60%
  - on average, 6.0% annually
  - year-on-year increases ranged from 2.2% (2010/11 to 2011/12) to 9.2% (2008/09 to 2009/10)
- **volume** increased by 30% in total
  - on average, 3.4% annually
  - year-on-year increases ranged from 0.7% (2010/11 to 2011/12) to 5.6% (2009/10 to 2010/11)
- **costs** increased by 23% in total
  - on average, 2.6% annually
  - one year of negative growth, 2009/10 to 2010/11, -1.4%

Findings from the literature review – A&E expenditure

Two studies considered drivers of A&E expenditure or utilisation, neither of which was from the UK.

Deb and Norton (2018) tested a range of models to test the effect of the Affordable Care Act (ACA) on young adults [26]. Using difference-in-differences analysis, the authors showed that emergency department visits were significantly lower in individuals who were insured as a result of the ACA's young adult expansion. The size of the treatment effect varied across models, but the hurdle model showed the effect resulted from a lower probability of presentation, rather than a lower level of activity amongst attendees. The authors included a range of control variables, but reported only the effects of health status: those with better physical or better mental health status were significantly less likely to present at the ED and attendees with better health also had fewer presentations [26].

Dinh et al. (2016) examined emergency department visits in Australia [32]. They found ED presentations increased over the study (2010 to 2014) at a rate that was disproportionate to rises in the population. The highest rate of increase in ED presentations was in those 85+.

Specialist Services

Trends in expenditure on specialist services

This setting represents 4.1% of total NHS expenditure in 2016/17 and comprises four different services: adult critical care, specialist palliative care, cystic fibrosis and cancer multidisciplinary team meetings (the latter included only since 2011/12).

From 2008/09 to 2016/17:

- **total expenditure** increased by 35% in total
  - on average, 3.8% annually
  - year-on-year growth rates ranged from 0.1% (2010/11 to 2011/12) to 7.6% (2008/09 to 2009/10)
- **volume** increased by 22% in total
  - on average, 2.5% annually
  - year-on-year growth rates ranged from 0.5% (2014/15 to 2015/16) to 6.1% (2008/09 to 2009/10)
- **costs** increased by 11% in total
  - on average, 1.3% annually
  - two years of negative growth
  - year-on-year growth rates ranged from -2.7% (2010/11 to 2011/12) to 6.6% (2013/14 to 2014/15)

Findings from the literature review – specialist services

Hakkinen et al. (2008) used data from Finland to explore drivers of utilisation of, and expenditure on, specialist inpatient and outpatient care [40]. In community-dwelling people aged 65 and over, the likelihood of utilisation decreased with age and time to death (TTD). Morbidities – captured by 18 assorted chronic conditions – were associated with a higher probability of utilisation, particularly in those with cancer. Expenditure rose with age, but the effect was not linear and depended on the model specification. Expenditure on specialist care was higher in those who died compared to survivors. The effect of a cancer diagnosis on expenditure was mixed (varying by cancer type).

In an Australian study of out-of-hospital care, Moorin et al. (2012) found the relationship between age and expenditure on specialist services was non-linear, being positive as the final year of life approached and then turning negative in the last few months of life [51]. This probably reflects a move towards best supportive care as treatment response declined.

Diagnostics and therapeutics

This setting covers chemotherapy, radiotherapy, high cost drugs, radiology, diagnostic tests and renal dialysis. The categories used to describe chemotherapy, radiotherapy, and high cost drugs have been subject to substantial revision over time. Since 2013/14, categorisation has been fairly stable for all three types of activity.

We found few patient-level studies assessing the impact on expenditure on these technologies. Sorenson et al. (2013)'s review of medical technologies described the evidence base as 'sparse' and predominantly composed of descriptive or qualitative studies, with econometric studies failing to distinguish different types of technology (e.g. drugs versus devices) – probably due to a lack of relevant data [73]. The 86 studies reviewed by Sorenson et al. painted a mixed picture, suggesting the relationship between new technologies and HCE is complex, dynamic and both context-specific and technology-specific.

Chemotherapy

Trends in expenditure on chemotherapy

This setting[18] represented 1.6% of total NHS expenditure in financial year 2016/17.

From 2008/09 to 2016/17:

- **total expenditure** in chemotherapy grew by 113% and the mean growth rate for the period was 10%
- total volume rose by 110%
  - **volume** growth rates were large and positive between every pair of financial years; the average for the period was 9.9%
  - the minimum **volume** growth was 3.4% (between 2014/15 and 2015/16)
- **total cost** rose only by 1.4%. Cost growth rates appear cyclical, alternating between large positive and negative values. The mean cost growth for period was 0.4%

Findings from the literature review – chemotherapy

The literature review did not identify any individual-level analyses of factors driving chemotherapy expenditure. The availability and price of new technologies in England is directly influenced by the guidance from the National Institute for Health and Care Excellence [133], and payment systems also influence adoption and diffusion [73]. Sorenson et al.'s (2013) review of medical technology as a driver of HCE found that new cancer drugs often had significant financial impacts [73].

Radiotherapy

Trends in expenditure on radiotherapy

This setting represented 0.5% of total NHS expenditure in financial year 2016/17.

From 2008/09 to 2016/17:

- **total expenditure** increased by 43% in total
  - on average, 4.6% annually
  - one year of negative growth, 2014/15 to 2015/16, -1.7%
- **volume** increased by 72% in total
  - on average, annul growth was 4.6%
  - growth was negative in three years
  - year-on-year growth rates ranged from -2.7% (2015/16 to 2016/17) to 14.0% (2008/09 to 2009/10)
- **costs** decreased by 17% in total
  - on average, -2.2% annually
  - five years of negative growth
  - year-on-year growth rates ranged from -9.4% (2009/10 to 2010/11) to +3.9% (2012/13 to 2013/14)

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[18] Prior to 2008/09, chemotherapy Healthcare Resource Groups (HRGs) were based on courses of treatment rather than cycles [132]. In the new system, each patient receives a regimen (procurement) HRG plus a delivery HRG, with the exception of 'non same-day inpatients' whose delivery costs are assumed to be covered by the inpatient HRG. The unbundling of chemotherapy HRGs also reduced HRG costs for admitted and non-admitted care.

Findings from the literature review – radiotherapy

The literature review did not identify any analyses of factors driving expenditure on radiotherapy.

High Cost Drugs (HCD)

Trends in HCD expenditure

This setting represented 2.5% of total NHS expenditure in financial year 2016/17. HCD capture treatments that are administered in the inpatient, outpatient and other settings. HCD are unbundled Healthcare Resource Groups (HRGs) and capture drugs whose cost is disproportionally high and only relate to a limited number of patients. The drugs on the list vary by year, but in general are used to treat patients with cancer, hepatitis C, HIV, transplant patients, juvenile arthritis and cystic fibrosis among others.[19]

HCD in Reference Costs include treatments directly commissioned by NHS England, as well as drugs funded through the Cancer Drug Fund.

From 2008/09 to 2016/17:

- **total expenditure** on High Cost Drugs rose by 230% with a mean growth rate of 16.7%
  - The total growth between 2008/09 - 2009/10 was unusually large (45.8%). For that pair of years, growth in volume and cost were 30.1% and 12.1% respectively
- **total volume** rose by 270%
  - the mean volume growth for the period was 18.0%
  - annual growth rates generally exceeded 15.0%, with the exception of 2014/15 – 2015/16 (7.0%) and 2015/16 –2016/17 (11.4%)
- **total cost** declined by 10.7% with a mean cost growth of -1.2%
  - cost growth rates were negative for every pair of years with the exception of 2008/09-2009/10 (12.1%) and 2014/15 –2015/16 (7.2%)

Findings from the literature review – high-cost drugs

The literature review did not identify any analyses of factors driving expenditure on HCD. Sorenson et al.'s review of medical technology as a driver of HCE found that new expensive technologies were more likely to be adopted by better resourced jurisdictions and that procurement policies also influenced adoption [73]. In other words, uptake appears to be largely driven by supply side factors.

Radiology

Trends in expenditure on radiology

This setting represented approximately 1.3% of total NHS expenditure in 2016/17.

From 2008/09 to 2016/17:

- **total expenditure** increased by 34% in total
  - on average, 3.8% annually
  - two years of negative growth
  - year-on-year growth rates ranged from -5.1% (2009/10 to 2010/11) to 11.0% (2014/15 to 2015/16)
- **volume** increased by 40% in total
  - on average, 4.3% annually

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[19] https://www.england.nhs.uk/wp-content/uploads/2017/04/nhs-england-drugs-list-v14.pdf

- o   one year of negative growth
- o   year-on-year growth rates ranged from -0.7% (2010/11 to 2011/12) to 9.3% (2014/15 to 2015/16)
- **costs** decreased by 4% in total
  - o   on average, -0.5% annually
  - o   four years of negative growth
  - o   year-on-year growth rates ranged from -5.7% (2009/10 to 2010/11) to 3.1% (2011/12 to 2012/13)

Findings from the literature review – radiology

There was no study that specifically evaluated predictors of expenditure on radiology, but this service was included in the analysis of diagnostic and therapeutic services by Moorin et al. (2012) [51].

Diagnostic Tests

Trends in expenditure on diagnostic tests

This setting represents approximately 1.2% of total NHS expenditure in 2016/17.

From 2008/09 to 2016/17:
- **expenditure in diagnostic tests** rose by 47% in total, equating to a mean annual rise of 5.1%
- **total volume** rose by 59.0% with a mean annual growth of 6.2%
  - o   volume growth rates between the pair of years 2010/11 -2011/12 and 2012/13 – 2013/14 were unusually large and equal to 17.6% and 15.5% respectively
- **total cost** declined by 7.4%
  - o   year-on-year cost growth rates fluctuated between negative and positive values, with a mean annual growth of -0.8%
  - o   cost growth between 2012/13 – 2013/14 was a notable outlier (-11.3%)

Findings from the literature review – diagnostic tests

In an Australian study of out-of-hospital care, Moorin et al. (2012) examined factors driving expenditure on diagnostic and therapeutic services (pathology, radiology, allied health treatments). In the years approaching death, the relationship between TTD and expenditure on diagnostic tests was positive and linear. The relationship between age and expenditure was non-linear, being higher in younger age groups and lower in older people [51].

Renal Dialysis

Trends in expenditure on renal dialysis

This setting represents approximately 0.7% of total NHS expenditure in 2016/17.

From 2008/09 to 2016/17:

- **total expenditure** in renal dialysis has risen by 16% with a mean annual growth rate of 1.9%
- **volume** shows a negative trend and declined by 1% in total
  - o   the mean growth rate was -0.1%
  - o   since 2014/15 -2015/16 volume growth has been positive and over 2.0%.
- **cos**t rose by 17.3%, equating to a mean annual rise of 2.0%

Findings from the literature review – renal dialysis

The literature review did not identify any analyses of factors driving expenditure on dialysis. However, this is likely to be related to the prevalence of chronic kidney disease (CKD) – which is in turn related to the prevalence of other conditions, particularly diabetes and hypertension. Dieleman et al. (2017) found that when adjustments were made for comorbidities, the cost of CKD increased by 74% (the largest increase of any of the 154 diseases studied) [31].

Mental Health services

Trends in expenditure on mental health services

The measurement of mental health activity changed in 2011/12 with the introduction of MH Clusters, therefore we can only calculate growth for this setting since that year using the information recorded in the Reference Costs. This setting covers activity recorded for adults in mental health care clusters (admitted patient care, non-admitted and initial assessments), children and adolescent mental health services, drug and alcohol services, mental health specialist teams, secure and specialist mental health services.

This setting represents approximately 7.1% of total NHS expenditure in the financial year 2016/17. From 2011/12 to 2016/17:

- **total expenditure** increased 6% in total
  - two years of negative growth and three years of positive growth
  - year-on-year growth rates ranged from -6.9% (2011/12 to 2012/13) to 9.2% (2014/15 to 2015/16)
- **volume** increased by 9% in total
  - year-on-year growth rates ranged from -1.0% (2012/13 to 2013/14) to 5.7% (2014/15 to 2015/16)
- **costs** decreased by -3% in total
  - year-on-year growth rates ranged from -6.5% (2011/12 to 2012/13) to 3.3% (2014/15 to 2015/16)

Findings from the literature review – mental health services

The factors influencing need for mental health services are conventionally assumed to differ from those driving demand for general acute care [10]. Although several studies in our review included psychiatric services in their measure of HCE [19, 42, 44, 57, 58] only one reported determinants specific to a mental health care setting, institutional mental health care [40]. In their Finnish study, Hakkinen et al. (2008) reported a subgroup analysis of drivers of psychiatric inpatient care. The authors excluded people receiving long-term care and used a two-part model to separate factors driving utilisation from those driving expenditure.

The probability of utilisation increased with age but the level of expenditure decreased with age. In both, the effect was smaller when proximity to death was taken into account. Those who died also had a higher probability of using psychiatric care and incurred higher expenditure than survivors; longer TTD was associated with a lower probability of utilisation and lower expenditure. Compared to males, being female was predictive of higher probability of use and higher expenditure. Higher income was associated with lower utilisation and lower expenditure on psychiatric inpatient care, though the effects were very small. Chronic conditions associated with higher use of (and expenditure on) mental health services included Severe Mental Illness (unsurprisingly), Parkinson's disease, diabetes and epilepsy. Findings for other chronic conditions were mixed, and difficult to interpret: for example, it is not clear why asthma or rheumatoid arthritis would be risk factors for using psychiatric care. A possible explanation is the coefficients on the 18 morbidities are biased due

to omitted variables, as the study did not control for some common conditions such as dementia [40].

Primary Care

Trends in primary care expenditure

Primary care is one of the largest settings in the NHS and accounted for 10.4% of the total expenditure in 2016/17.

There is no comprehensive and exhaustive dataset, akin to Reference Costs, for primary care[20] so our estimates of consultations are based on survey measures: initially the General Lifestyle Survey (GLS), but from 2010/2011 onwards, the GP Patient Survey (GPPS). Hence, primary care figures need to be interpreted with caution. Moreover, there is a break in the series due to a change in methodology: from 2012/13 onwards, the total number of consultations also include patients who had seen a primary care nurse.

From 2008/09 to 2012/13:

- **total primary care expenditure** rose by 30% and the average growth rate for the period was 7.1%
- total **primary care volume** rose by 4% with a mean growth rate of 1.0%
- total growth for **costs** was much larger and equal to 25% with a mean growth rate of 5.9%

From 2012/13 to 2016/17:

- **total primary care expenditure** declined by 17% and the average growth rate for the period was -4.0%
- total **primary care volume** declined by 1% with a mean growth rate of -0.2%
- total growth for **cost** declined by 16% with a mean growth rate of -3.9%

Findings from the literature review – primary care expenditure

Our review identified seven studies that reported drivers of primary care expenditure or use [17, 22, 26, 30, 47, 51, 62]. All studies controlled for age and gender, six adjusted for morbidity and three for time-to-death (TTD).

Primary care generally included GP visits, referrals, prescriptions and tests, but cross-country differences were evident. In the US, evidence was limited to studies of 'office-based visits', which may not be equivalent to GP visits. A French study included optometry, prostheses and orthotics in its measure of primary care [62], and an Italian study included tests, prescriptions and specialist visits but (strangely) excluded GP visits [17].

As expected, morbidity was identified as an important explanatory variable for individual primary care costs. In a UK study, Brilleman et al. (2014) [22] tested various measures of patient morbidity to see which explained most variation in primary care costs. Those based on measures from the Quality and Outcomes Framework (QOF) performed better than measures based on the Charlson index. The best performing multimorbidity measures were simple counts of the number of chronic conditions or simple sets of disease dummies. Similarly, DeSalvo et al. (2009) used US data to compare the predictive performance of four health outcome indices. In this US population, a simple model with

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[20] More information on the estimation method can be found in Bojke et al. (2017) [15].

self-rated health and age performed well as the more complex models in predicting people at risk of higher levels of expenditure on office-based visits [30].

Lapi et al. (2015) developed a casemix index based on interactions between age, gender and acute and chronic conditions. The index explained over half of the variation in Italian primary care costs [47]. Another Italian study by Atella et al. (2014) found the Charlson index score predicted both utilisation of and expenditure on primary care [17]. Focusing on young adults, a US evaluation by Deb and Norton (2018) showed that office-based visits to medical practitioners were less likely to occur, and the number of visits was lower amongst attendees, in people with better physical or mental health status [26]. Thiébaut et al. (2009) found health status was the strongest predictor of ambulatory care use (health seeking behaviour) in France, followed by age, female gender and private health insurance status [62]. This French study also used a microsimulation model to project national ambulatory expenditure: it was projected to rise annually by 1.18% in the base case (no change in morbidity or technology), by 0.95% assuming healthy aging (morbidity compression), and by 1.38% with life-extending technological innovation [62]. The authors concluded that healthy aging is unlikely to be sufficient to curb growth in primary care expenditure, and noted that the effects of an ageing population may be even greater for hospital expenditure or LTCE.

Three studies took account of time-to-death (TTD) on primary care expenditures [17, 51, 62]. Thiébaut et al. (2009) used a simple morbidity-mortality index constructed from a measure of vital risk and a disability index [62], whereas the others used proximity to death. Even after controlling for time-to-death, aging remained a strong driver of primary care costs in Italy [17] and Australia [51], with the latter study identifying a clear linear relationship.

Only one study adjusted for deprivation, which was associated with higher primary care expenditure after controlling for age, gender, practice effects and/or comorbidity. The finding was consistent across a range of models, which may be indicative of "horizontal pro-poor inequity" [22].

Evidence from France showed that private health insurance status was associated with ambulatory care use [62]; similarly, the US difference-in-differences analysis by Deb and Norton (2018) found that office-based visits to medical practitioners were significantly higher in young adults who became insured as result of the Affordable Care Act [26].

Community-based settings

Community Prescribing

Trends in community prescribing expenditure

Community prescribing – prescriptions written by GPs, nurses or other health care professionals who work in the community – is one of the largest settings in the NHS and accounted for 10.9% of total expenditure in 2016/17. We observe a modest expenditure growth figure that masks large variations in volume and cost growth.

From 2008/19 to 2016/17:

- **pharmaceutical expenditure** rose by 10% in total, equating to a mean annual rise of 1.2%
- **total prescribing volume** grew by 45% with a mean growth rate of 4.8%
- **prices** of pharmaceuticals have been decreasing year-on-year: total decline of 24% with an average growth rate of -3.4%
- **cost growth** rates between the years 2011/12 – 2012/13 and 2015/16 – 2016/17 were -7.2% and -7.0% respectively

The reduction in pharmaceutical prices reflects the progress with the implementation of generic prescribing, e.g. the share of generics market in the UK is among the highest in Europe, the effects of the Price Regulation Schemes and the incremental use of health technology assessment.

Findings from the literature review – community prescribing

Seven studies reported factors driving pharmaceutical spend in the community [21, 28, 30, 40, 43, 50, 63]. None of the studies was from the UK.

De Meijer and colleagues (2013) used decomposition analysis to understand changes in community pharmaceutical expenditure [28], such as drugs prescribed at outpatient clinics or by GPs, in the Netherlands. Community pharmaceutical expenditure rose by 69% over the study period (2004 to 2013). Decomposition analysis indicated that expenditure growth occurred mainly at the top of the distribution and was driven principally by structural shifts (such as technological progress – for example, the highest cost cases were treated with even more expensive drugs). Changes in the distribution of determinants, such as population ageing and a rise in the number of outpatient visits, played a lesser role but were also important. For cases at the lower end of the expenditure distribution, structural shifts were the principal reason for lower spending (due to the withdrawal of contraceptive drugs from the benefits package).

Hill et al. (2010) tested six different models using US data on privately insured adults and on older people. They used diabetes as an example to show how effects were model-dependent [43]. For privately insured adults, the effect size of diabetes on prescription drug expenditure varied across the six models by a factor of two; for older people, the effect varied by a factor of 1.5. Results for other conditions were reported to be 'similar' but no details were given.

Three studies showed that the effects of age on prescribing expenditure were smaller when models controlled for time-to-death (TTD) [40, 50, 63]. Moore and colleagues (2014) examined medication expenditure in older people in New Zealand [50], matching decedents to survivors. Proximity to death was a more important driver than age: medication expenditure for decedents was, on average, between 1.82 and 2.09 times higher than for matched controls (survivors). However, age was still a factor driving the per person cost of prescription drugs: those dying in their 90s consumed fewer drugs and had a lower mean expenditure than people dying in their 70s or 80s.

Two studies employed relatively simple models. Blanco-Moreno et al. (2013) plotted Spanish data showing that pharmaceutical spend per head was 'J-shaped' with respect to age and, on average, higher in females in all age groups [21]. DeSalvo et al. (2009) compared the predictive performance of the general self-rated health questionnaire with three morbidity indices. In this US population, a simple model with self-rated health and age performed well as the more complex models in predicting people at risk of higher levels of pharmacy expenditure [30].

Thiebaut and colleagues (2013) report a microsimulation exercise to estimate the effects of changes in health status and in life expectancy on publicly reimbursed drug expenditure in France over a 25 year period [63]. To capture health status, the authors generated a composite indicator from two measures: vital risk (i.e. risk of death) and disability level linked to a chronic condition. Outpatient (ambulatory) drug expenditure excluded hospital drugs and over-the-counter medications. At the individual level, changes in health status were the strongest predictor of drug expenditure and the impact of age, after controlling for health status, was small. At the national level, population ageing was predicted to have a significant positive effect on aggregate pharmaceutical expenditure, with predicted annual growth rates of between 1.14% and 1.77% depending on assumptions about life expectancy and morbidity [63].

A Finnish study evaluated the effect of age, gender, death, TTD, income and morbidities on outpatient prescribed medicines for people 65 and over [40]. Hakkinen et al. (2008) found that age was predictive of a lower likelihood of use, but of higher expenditure in users. However, the impact of age was non-linear, both on utilisation and spend. Females were more likely to receive prescribed medicines, but their medication expenditure was lower than men's. Longer TTD was associated with lower expenditure. In the main, morbidities were linked to higher likelihood of utilisation and to higher spend.

Community Care

Trends in community care expenditure

Community care accounted for approximately 6.3% of the total expenditure in the NHS in the year 2016/17. Examples of services captured in this setting are: activity performed by allied health professionals, health visiting and midwifery, nursing or wheelchair services, among others.

From 2008/19 to 2016/17:

- **expenditure on community care** rose by 35%, equating to a mean annual rise of 4.0%
- **volume** grew by 19% in total with a mean growth rate of 2.4%
  - growth in **activity** has been volatile due to introduction of new categories and the reclassification of others
  - an example is the large increase in volume between 2012/13 and 2013/14 (17.4%) that resulted from the introduction of three types of activity – community intermediate care activity, wheelchair services and other therapists – that were previously unrecorded (Bojke et al., 2016) [134]
- total **costs** rose by 14% with a mean growth rate of 1.6%

Findings from the literature review – community care

The literature review did not identify any analyses of factors driving expenditure on community care (besides those examining community prescribing).

Optometry and Dentistry

Trends in expenditure on optometry and dentistry

Optometry and dentistry accounted for approximately 2.3% of the total expenditure in the NHS in the year 2016/17. Dentistry services are categorised in bands (1, 2 and 3), urgent and other services. Optometry captures the total number of eye tests.

From 2008/09 to 2016/17:

- **total expenditure** in optometry and dentistry rose by 24% with a mean growth rate of 2.7%
- **total volume** rose by 7% with a mean growth of 0.9%
- **total cost** rose by 15.3% and the mean cost growth rate was 1.8%
  - The mean masks large year-on-year variation as until 2011/12 there was no growth in costs, whilst over the subsequent years the mean cost growth was 2.9%

Findings from the literature review – optometry / dentistry

No study of drivers of expenditure on optometry or dentistry was identified, although some studies included these in their measures of primary care or ambulatory care spend, e.g. Thiébaut et al. (2009) [62].

Rehabilitation

Trends in rehabilitation expenditure

This setting represents approximately 1.1% of total NHS expenditure in 2016/17 and comprises complex, specialised and non-specialised rehabilitation services.

From 2008/09 to 2016/17:

- **total expenditure** increased by 10% in total
  - on average, 1.5% annually
  - two years of negative growth
  - year-on-year growth rates ranged from -14.7% (2010/11 to 2011/12) to 9.3% (2012/13 to 2013/14)
- **volume** decreased by 2% in total
  - on average, -0.1% annually
  - four years of negative growth
  - year-on-year growth rates ranged from -10.4% (2010/11 to 2011/12) to 12.1% (2012/13 to 2013/14)
- **costs** increased by 13% in total
  - on average, 1.6% annually
  - three years of negative growth
  - year-on-year growth rates ranged from -5% (2010/11 to 2011/12) to 6% (2011/12 to 2012/13)

Findings from the literature review – rehabilitation

The literature review did not identify any analyses of factors driving expenditure on rehabilitation.

Other

Trends in expenditure on other services

This setting captures other type of activity reported in the Reference Costs data. In recent years, it includes the following activities: Regular Day and Night Admissions (RDNA), Audiology Services, Day Care Facilities and Hospital at home/Early discharge schemes. The classification of these activities has changed over time and some types of activity are occasionally discontinued, or subsumed under other broad categories (Castelli et al. 2018) [14].

This setting represented 0.4% of total NHS expenditure in 2016/17.

From 2008/19 to 2016/17:

- **expenditure** decreased by 14% in total, equating to a mean annual growth rate of -1.7%
- **volume** decreased by 14% in total with a mean growth rate of -1.7%
  - growth in **activity** has been volatile due to introduction, discontinuation and reclassification of categories
  - the largest decrease in volume growth was between the financial years 2012/13 and 2013/14 (-13.7%)
- total growth for **cost** is negligible, equal to 0.2%, with a mean growth rate of 0.05%
  - the figure above masks large year-on-year variations
  - Negative growth is observed from 2014/15 onwards

Findings from the literature review – other factors

The literature review did not identify any analyses of factors driving expenditure on the items in the 'Other' category.

Towards a projections model of health care expenditure

Below, we set out lessons emerging from the literature review and the analysis of trends in HCE. These offer potential insights for building projection models of health care demand.

Mechanisms that shape demand are complicated, and may be complex

The way that factors drive health care utilisation and expenditure is complicated, and could even be described as 'complex' [135]. A complicated process is one that involves a set of interrelated parts that function in a broadly predictably way. In contrast, in complex systems the mechanisms through which the parts operate are dynamic, evolving, and interactive – and may include feedback loops.

Effects are likely to be non-linear (vary across the distribution), but there is some inherent unpredictability involved in the process of 'projecting' future expenditures and future demand for health care – not simply uncertainty around point estimates of effect size. To illustrate: new technologies such as genomics, remote monitoring, telemedicine, automated image interpretation and robotics have potential to change how the NHS operates and delivers in future, but no one knows for sure how this 'digital transformation' will pan out or what it may mean in terms of the structure and level of future expenditures [136].

Methodology matters

Identifying the factors driving demand is just a first step: the way they are measured and the model with which they are analysed are likely to affect their projected effects on future demand. Potential interactions are also important to capture.

There is strong evidence that the estimates of effects are sensitive to <u>model specification</u>, particularly the choice of link function when modelling positive expenditures. Hill et al. (2010) tested six models to compare their performance, and reported average marginal effects for service users with long-term conditions [43]. In all models, having a chronic condition increased total spend and spend on prescription drugs, but the magnitude of the effect varied widely across models, across different age groups, conditions and types of expenditure [43]. Experience in understanding data and appropriate model specifications is required to model health care demand.

Several studies showed that results depend on how individual <u>covariates are measured</u> and modelled [22, 30]. For example, the way morbidity and comorbidity (the interactions of different morbidities) are treated can influence effect size [25, 31].

<u>Omitted variables</u> can lead to biased estimates. A consistent finding across the studies of HCE is that the relationship between age and expenditure is smaller – or even non-significant – when comorbidities, disability or TTD are taken into account. Evidence on the size and importance of this effect appears inconclusive and seems to vary by care setting. Age is, of course, itself a predictor of comorbidity and TTD, i.e. it is correlated with other explanatory variables. When making long-term projections, it will therefore be important to establish whether, and to what extent healthy ageing can counterbalance expenditure rises due to an ageing population.

The pathway linking demand to HCE needs to be explicit

Drivers of <u>utilisation</u> may differ from drivers of <u>expenditure</u> – even within the same care setting [26, 36, 52], though evidence from a single study suggests drivers of utilisation and level of utilisation are more similar when considering drivers of primary care visits [26].

Principal agent theory offers a helpful starting point to understand this process. In the main, patients (principals) take the initial decision to <u>utilise</u> care, with the decision on the <u>level and scope</u> of care – and hence its cost – taken by the clinician (agent). This theory is cited as a motivation for the use of two-part models to understand health care expenditure, but the characterisation is over-simplistic. Examples of instances in which the agent initiates the decision to utilise include:

- Proactive invitations to the patient to present for primary / secondary preventative care
- Referral to treatment decisions[21]
- Emergency or crisis situations in which the patient lacks capacity to make a decision

Shared decision-making is an example of the principal being involved in determining the level and or scope of care. These 'exceptions' to the principal-agent rule point to the need for clarity on the economic theory underpinning a model.

Simulation models are one way of making the pathway from demand to supply explicit [77]. A subset of studies employed simulation methods for either long-term care [49, 137] or HCE [45, 48, 62, 63, 65, 66]. These models have a number of potential advantages compared with 'standard' methods [138]. When applied to health care, simulation models can:

- incorporate dynamic relationships, capturing interactions and feedback loops
- accommodate variation in treatment effects for different subgroups
- identify spillover effects within health care settings and across settings
- explore the potential effects (and cost-effectiveness [77]) of new policies, via their expected impact on disease prevalence or risk factors

Drawbacks of microsimulation are their reliance on large datasets, and their need for extensive technical expertise and computing infrastructure. Health models seldom include behavioural components, and future research is needed to explore how these can be added without limiting generalisability. Reviews highlight a trade-off between complexity and comprehensiveness [138] and between the detail of the model and its predictive power [77].

The performance – in terms of added value and reliability – costs and feasibly of a microsimulation model should be considered very carefully before any decision is made to embark on this undertaking.

Data challenges should not be underestimated

Even if the factors that drive demand for health care, or that drive HCE, could be identified with certainty, models are dependent on the quality, availability and coverage of routine datasets and surveys.

Routine data may omit important factors that are harder to measure such as person-level social care, informal care, changes in the labour market, frailty and functioning, or public expectations.

Data are also subject to recording or measurement bias. For example, if the observed prevalence of comorbidities rises, it is unclear how much of this is a true increase and how much a change in reporting (perhaps triggered by changing patient classification systems).

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[21] In England, patients have a choice of hospital for elective referrals but may not be offered a choice of whether they are referred.

When reporting projections of HCE, uncertainties should be quantified where possible. Gaps in the data and, where applicable, the assumptions used to enable models to run should be acknowledged clearly and explicitly. There also needs to be transparency where uncertainties cannot be quantified: for example, poor quality or incomplete individual-level data for a particular care setting, or the potential for (unknown) bias perhaps due to missing variables that have not been previously tested.

Discussion

Overview of findings

In attempting to understand health care expenditures, a number of different approaches have been adopted according to the aggregation of data being considered.

Studies that focus on overall expenditure highlight the role of wealth, income (per capita GDP) or public expenditure as driving factors of health care expenditure. More recently, the important role of new technology as a driver of HCE has been recognised.

Studies that focus on expenditure for individuals demonstrates that morbidity and frailty [61] are important predictors of health care expenditure (HCE) [22, 25, 30, 31, 57]. Disability is a driver of long-term care expenditure (LTCE) but the impact of morbidity on LTCE appears to vary by condition [27].

Many studies have tested the relationship between time-to-death (TTD) and expenditure. When TTD is included in the model, the effect of age is usually reduced [37, 38, 40, 50, 63, 65], although evidence on the size and importance of this effect is inconclusive and seems to vary by care setting. Evidence from England showed that TTD dominated age as a driver of inpatient expenditure, but that morbidity dominated TTD. However, other studies on people at the end of life showed that age was still important: utilisation and spend were higher in younger than in older decedents. A Dutch analysis showed the predictive power of TTD varied by disease: for example, it was strongly predictive of higher inpatient expenditure for cancer patients, but performed less well for nonlife threatening conditions [65]. TTD as an explanatory variable for LTCE appears to be dominated by disability [27]. However, even after adjusting for TTD, age appears to remain important in explaining expenditure on both primary care [17, 51] and community prescribing [40, 50, 63].

Studies that tested for non-linearity in the effects of age on HCE showed that per capita expenditure was generally lower in older groups than in younger groups, for instance expenditure on inpatients at the end of life [59], on community prescribing [40, 50] on outpatients [21] and on mental health [40, 50].

Studies that distinguished drivers of utilisation from drivers of expenditure found little overlap between the determinants.

Gaps in the evidence base

Our review revealed an absence of evidence from the UK for many health care settings. Multiple studies examined inpatient and primary care settings, but only one study distinguished the effects of changes in the mix of elective and emergency care on HCE. We identified no UK individual-level studies exploring HCE drivers in outpatient settings, A&E, specialist or mental health care, and no study that examined drivers specific to elective inpatient or emergency inpatient settings. The influence of social care and informal care was rarely considered.

Evidence on technological drivers, particularly high cost drugs, was very limited – we found one literature review [73], a small number of aggregate studies [71, 90, 108, 123, 124] but no individual-level studies. This evidence gap is important, because English expenditure on chemotherapy and high cost drugs has increased substantially over the last decade.

Some factors that are likely to drive demand were not assessed in the literature. These include public expectations and wasteful use of resources.

Public expectations relate to the unwritten social contract between the NHS and citizens. The NHS Constitution sets out some broad and specific rights but falls short of approaches by social health insurance systems that specify a 'health basket' defining entitlement [139]. In the NHS, entitlement to care is more often interpreted indirectly, via explicit guidance by NICE and implicitly by policies that emphasise patient-centred or integrated care.

As new technologies, new treatments and new drugs develop, the NHS's ability to supply healthcare increases, but at the same time encourages demand. In part, this occurs through increasing population awareness of the benefits of consuming healthcare services. A concern is that this may lead to problems of moral hazard – individuals, aware that services are free at the point of access, fail to accept responsibility to manage their own health and avoid risks that the healthcare system is designed to insure against. For example, continuing to smoke when lung infections can be easily treated with antibiotics; failing to manage weight when prescriptions drugs to regulate high blood pressure or diabetes are readily accessible. In addition, as new technologies become available, involving less invasive procedures with lower time costs associated with undergoing treatments, expectations of the benefits that healthcare has to offer may further fuel demand. Some technologies, however, such as the development of remote monitoring that aids users with long-term conditions to manage better their illness without accessing services, are likely to mitigate demand and ease pressure on the healthcare system. This is irrespective of whether such technologies influence self-care and investments in health in a positive way or further promote a sense that healthcare can solve all health issues.

There appears to be little evidence on the impact of changing expectations of the benefits of healthcare and the impact this has on demand and in shaping health behaviours. Surveys of expectations tend to focus on the responsiveness of health services, such as whether patients feel they were treated with respect and dignity; views on cleanliness of facilities; speed of access; and overall patient satisfaction etc. While such aspects of healthcare delivery are important to users of services, at best, they only indirectly improve health outcomes. A recent poll of public opinion, however, suggests expectations of the use of health care might not be a cause for concern and that people are aware of funding constraints. [22] Of individuals polled, 58% agreed that there should be limits on what is spent in the NHS, while 44% thought that their own health is solely or mostly their responsibility, rather than the responsibility of the NHS. Younger people were most likely to agree that should people not look after their health, for example, by drinking too much, then the NHS could limit treatments for conditions resulting directly from their behaviours. More research evidence is required on how healthcare is perceived and the ways in which this influences the behavioural choices individuals make that affect their health.

We also found no specific evidence on wasteful expenditure. According to the Health at Glance 2018 (OECD) report, one-fifth of health spending is wasteful [140]. Examples include missed appointments, avoidable admissions, duplication of services, delayed discharges and unnecessary expenditure on pharmaceuticals – some of which is linked to prescribing of cost-ineffective medications.

Strengths

Analysis of trends in English HCE have shown how much of changing expenditure was due to volume and cost. This provides a useful overview of variations across settings. The literature review encompassed a wide literature – almost 3500 papers – of which 115 studies were found. These analyses were enormously heterogeneous in terms of the type of expenditure(s) they considered, the explanatory variables they tested and the methodologies used. Their aims and research

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[22] http://www.ipsos-mori.com/researchpublications/researcharchive/2975/Public-Perceptions-of-the-NHS.aspx

questions were also very variable. However, we have conducted a structured review of these studies and drawn out key findings that we hope are useful. We have also set out the next steps for building a model to project HCE and considered how this might fit with existing models of LTCE.

Limitations

The heterogeneity of the studies makes it very difficult to compare their findings in a robust way, and it was not possible to synthesise their findings quantitatively. There were large gaps in the evidence for many care settings, and a dearth of studies from the UK.

Another limitation is that trends analysis uses data at HRG level rather than at individual level. We can describe trends in volume, cost and expenditure but only conjecture how the demand drivers found in the literature review impact those trends.

Future drivers

What do we know?

The factors identified in the review are likely to continue to drive demand, i.e. demographic factors, and clinical or disability factors. Supply side constraints such as the care settings, technological developments and staffing mix will affect and shape HCE and LTCE.

What is unknown?

With known factors, the uncertainty is about how relevant they will be – both in terms of changes in the factors themselves (e.g. population ageing) and how their relationship with HCE may change. We expect new technologies to emerge, but we do not know what they might be, when they will happen, or what their effects will be on HCE. Changes in technological drivers are particularly difficult to anticipate but can have substantial impacts on HCE. Examples include the introduction of anti-VEGF intravitreal injections [141] and genomic testing in breast cancer [142]. Indeed, genomic medicine is a classic example of a technology with potential to revolutionise population health, but where there is little evidence of its effect on disease incidence [143].

In addition, the literature was silent on some factors that would be expected to drive demand, such as public expectations and wasteful use of resources (see above, Gaps in the evidence base).

Unknown unknowns

Major new factors may arise in the future, for example new disease, epidemics or acts of terrorism. Whilst these cannot be predicted, modelling exercises could use information from planning undertaken as part of health protection efforts.

Next steps

The key challenge for a health care (HC) projections model is that the system is complex and diverse and involves consideration of flows (e.g. GP consultations, hospital admissions) and stocks (waiting times). It will therefore be essential that the HC model is developed in stages, focusing sequentially on different conditions/clinical areas.

PSSRU has developed a suite of models for making projections of demand for long-term care (LTC) for older people and younger adults. These models produce projections to 2040 and beyond of numbers of disabled people, numbers of users of unpaid care and formal services, public expenditure on services and social care workforce. In ESHCRU, we have used them to produce projections for Department of Health & Social Care (DHSC) and for Office for Budget Responsibility (OBR)[137].

Many drivers of LTC demand are also associated with increased need for health care. The HC demand model will build on and, to some extent, replicate key features of the LTC models. We will thus ensure that the model for HC projection is consistent with the LTC models. This will facilitate examination of the impact of changes in the configuration of the health and social care system.

In addition, it will allow consistent scenarios to trends in drivers of demand (e.g. demographic pressures, compression of morbidity) to be tested across health and social care. These consistent projections across health and social care will be invaluable for informing strategies for system reform.

Whilst latent (or unmet) need is important, in practice the scope of the 'core' model may need to be defined by supply side constraints, i.e. what is funded by the NHS, and to what extent services are provided. Alternative modelling scenarios could incorporate estimates of unmet demand; avoidable demand, in which the impacts of investment in prevention are explored; and the effects of reductions in supplier-induced demand.

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