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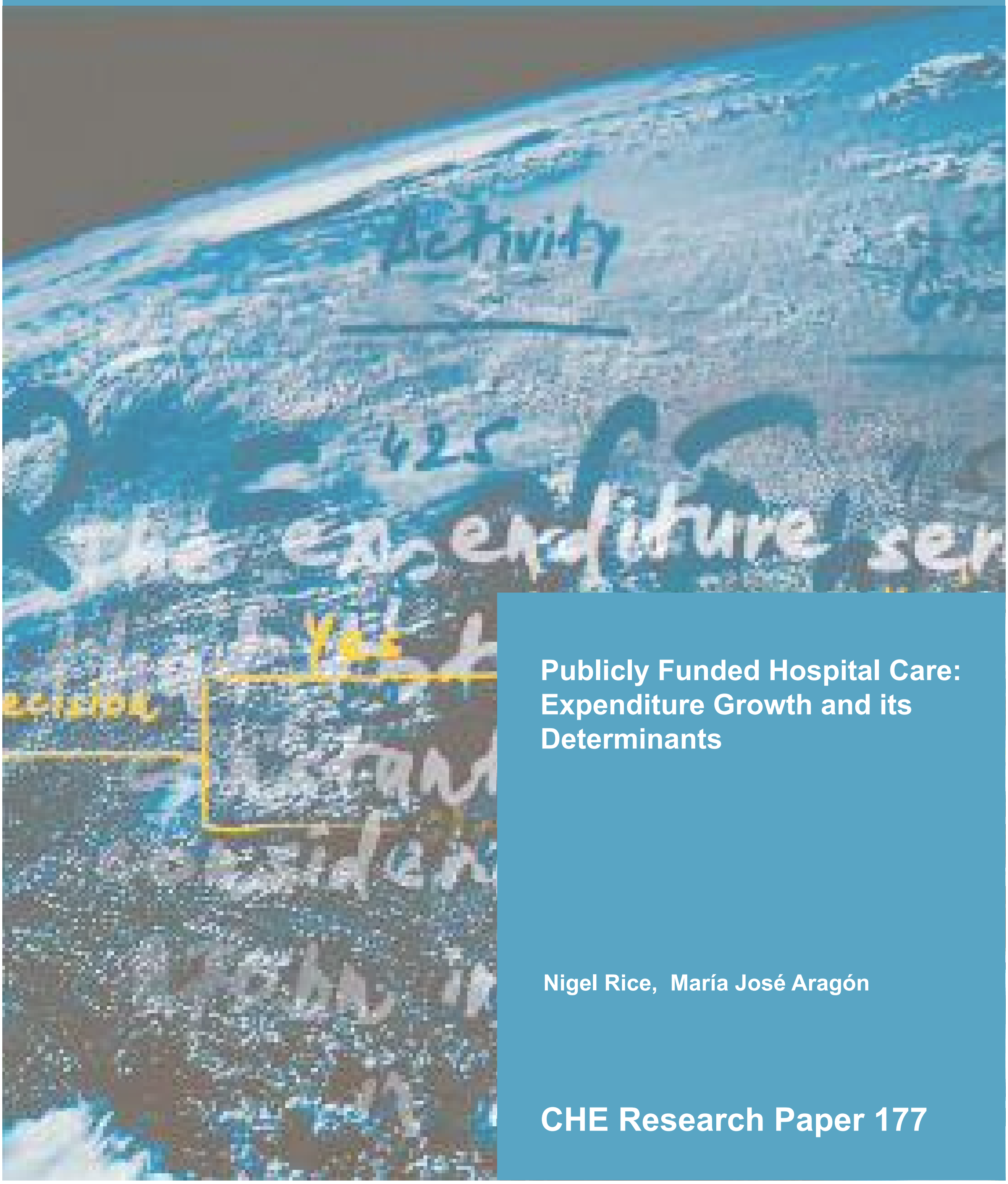

Publicly Funded Hospital Care: Expenditure Growth and its Determinants

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Abstract

Understanding the drivers of growth in health care expenditure is crucial for forecasting future health care requirements and for the efficient use of resources. We consider total hospital admitted care expenditure in England between 2009/10 and 2016/17. Decomposition techniques are used to separate changes in expenditure into elements due to changes in the distribution of characteristics, of both individuals and the services they receive, and due to changes in the impact of characteristics on expenditures. Growth in aggregate expenditure was due to increases in total patient admissions together with a substantial shift towards episodes of non-elective care, particularly the use of long-stay care. Decomposition of patient level expenditure suggests efficiency gains in treatment across the full distribution of expenditures, but that these were outweighed by structural changes towards a greater proportion of patients presenting with high-dimensional comorbidities. This is particularly relevant at the top end of the expenditure distribution and accounts for a large proportion of the total expenditure growth.

Keywords: Health Care Expenditure Growth, decompositions, Hospital Episode Statistics

JEL codes: C1; I1

1. Introduction and Background

The continued rise in health care expenditure (HCE) relative to national income has attracted a great deal of attention and raises important questions about the sustainability of health service provision and its ability to meet population health care needs. Since 1978-79 while UK public spending on health care rose by an average of 3.8% per year in real terms, the average growth of the economy was 2.2% per year (Licchetta and Stelmach 2016). In 2012 publicly funded HCE represented approximately 7.4% of GDP. The year-on-year rise in HCE is considered one of the greatest challenges to long-term fiscal sustainability.[1] Demand side factors such as changing demographics due to an ageing population, increases in chronic conditions and multiple comorbidities, and rising public expectations of the benefits of health care are often cited as key drivers of expenditures. On the supply side concerns include increasing relative health care costs, the impact of technological change and the configuration and efficiency of services provision. Exploring how these factors have changed over time and their relative contribution to expenditure growth is key to understanding the rise in HCE and for forecasting future expenditure requirements and the efficient management of resources.

This paper considers changes in expenditure for hospital admitted care in the context of a publicly funded health care system (the English National Health Service: NHS) over the period from 2009/10 to 2016/17. Note, that expenditure is proxied by costs of care derived from NHS Reference Costs; see section 3. Throughout we use expenditure and costs interchangeably. We explore how the observed growth in expenditure relates to changes in its determinants using individual-level administrative data. In both years secondary care, which includes hospital services, community care, mental health and ambulance services, accounted for around 62% of total HCE (Office for National Statistics 2019b). We consider changes to supply-side (or institutional) characteristics focusing on changes to the provision of services between elective and non-elective care admissions, and short and long-run stays and day cases, together with changes to demand-side factors including age, morbidity and the number of patients presenting for care. We supplement descriptive analyses with regression-based decomposition techniques that allow for greater scrutiny of the causes of observed changes in expenditure. We first apply Oaxaca-Blinder decomposition techniques (Oaxaca 1973) which facilitates the attribution of changes in expenditure to components due to structural changes, for example an ageing population or changing morbidity characteristics, and components due to a changes in the relationship between structural characteristics and health care expenditure (coefficient changes). These might arise due to changing input prices, technological progress, or more general efficiency gains. We then consider how these relationships varies across the full distribution of expenditures. This is important in understanding the relative impact of structural and coefficient changes at different parts of the distribution, and particularly at the top end where increases in the proportion of patients over time can have a substantial effect on expenditure growth.

Overall growth in expenditure between the period 2009/10 and 2016/17 was £3.5b. The corresponding growth in the number of admitted patients was 700,000. For supply characteristics, increases in episodes of non-elective care accounted for the majority of the increase in observed costs and was driven largely by increases in long-stay episodes of care. The main contributing demand-side factor was a substantial increase in the proportion of patients presenting with multiple comorbidities (5+), and which were predominantly located within older patients (70-80 and 80+ years age groups). These factors increased expenditures at the top of the expenditure distribution, particularly the upper 10%. While the proportion

[1] By fiscal sustainability we imply the ability of the health service to continue to meet population needs at a level of funding that is acceptable to the electorate. Clearly, the proportion of total government expenditure afforded to health care could increase beyond current levels, but this implies an opportunity cost to other public services that the electorate may not wish to support.

of older more complex patients rose over the period, decomposition analysis suggests that the per patient costs of treatment across all deciles of the expenditure distribution decreased. These efficiency gains are, however, outweighed by the increasing proportions of complex comorbid patients admitted to non-elective care.

2. Health care services in the UK

Health care delivery in the UK is predominantly provided by the NHS. Approximately 80% of care is financed through public funds which is derived from conventional income and expenditure taxes.[2] The UK NHS comprises four devolved administrations for each of England, Northern Ireland, Scotland, and Wales with block grants used to determine the level of public funding to each. The broad functional split for health care is between primary care (often termed Family Health Services) and secondary care (often referred to as Hospital and Community Health Services: HCHS). The latter accounted for approximately 61% and 64% of total (NHS) health care expenditure in 2009/10 and 2016/17 respectively (Office for National Statistics 2019b). HCHS covers all hospital treatments both for admitted patient care (patients who stay for at least one night as inpatients and day cases discharged on the same day as they are admitted) and outpatient care. Family Health Services largely covers the provision of general medical practice or ambulatory care which accounts for approximately 17% of expenditure. Since health care services are free at the point of use primary care physicians effectively act as gatekeepers which together with waiting and queueing for treatment regulate demand for secondary care services.

Recent reforms applied mostly in England (in the financial year 2003/04) have seen the adoption of fixed prices for hospital treatments, greater discretion over the use of funds by NHS hospitals and empowerment of patients through encouraging choice and ‘shopping around’. These changes have been evidenced to increase hospital activity (Charlesworth et al. 2014).

2.1. Basic trends in Health Care Expenditure

Government expenditure on health care as a proportion of GDP has more than doubled over the past 60 years from approximately 2.9% in 1958/59 to 7.1% in 2018/19 (Harker 2019). Focusing on the last decade, which included a large and sustained increase in health expenditures as a percentage of GDP, real NHS expenditure per capita increased over 30% for all four countries of the UK (HM Treasury 2010-2017), see Figure 1.

2.2. Changes in health care expenditures

Dormont et al. (2006) using data on a sample of individuals with public health insurance applied decomposition techniques to understand the sources of change in HCE between 1992 and 2000 in France. They considered expenditure on hospital care, physician consultations and prescriptions by ten-year age groups. Applying microsimulation techniques they calculated, for each type of expenditure and age group, the probability of having positive expenditures and the average predicted expenditure for those with positive health care utilisation. These estimates were then used to calculate the change in expenditure between the two years, separating the effect of changes in health care provision for a given morbidity from changes in the incidence of morbidity. Their results indicate that, for hospital care, changes in the provision of care contributed to increasing expenditure while changes in morbidity led to slightly reduced expenditures for people over 40 years of age.

More recently, de Meijer et al. (2013) analyse the change in the distribution of HCE (hospital care and pharmaceuticals) between 1998 and 2004 in the Netherlands using a combination of insurance claims,

[2] The remainder is privately financed with this split between public and private expenditure remaining fairly constant over time.

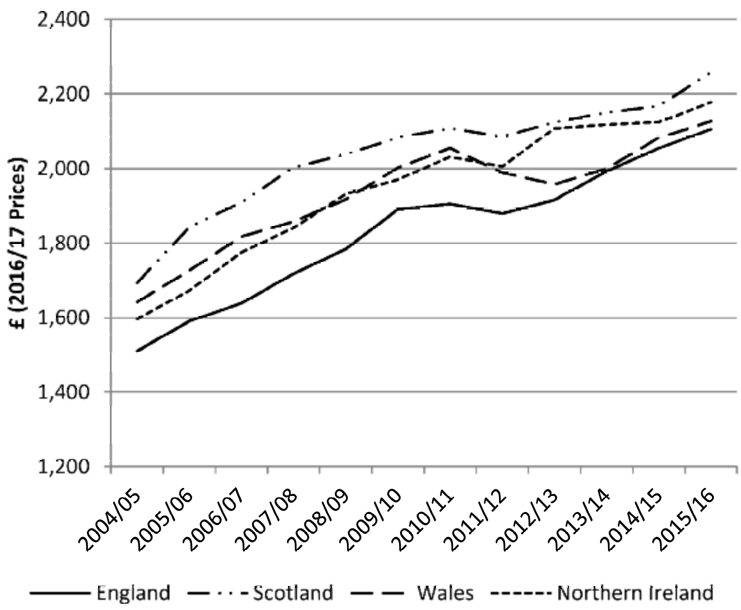

Figure 1: Health Care Expenditure per capita in the UK

hospital discharges and mortality data. Using the methodology proposed by Chernozhukov et al. (2012), they decompose the change in HCE across its full distribution. Their results indicate important differences in the impact of changes in characteristics and changes in their coefficients at different points across the expenditure distribution. For individuals with positive expenditure, both changes in characteristics and coefficients contribute to increasing expenditure throughout the distribution. However, their relative importance varies. At the bottom of the expenditure distribution both factors contribute equally, while at the top, the contribution of the change in coefficients is around one and a half times the contribution of the change in characteristics. For hospital care, the growth in expenditure over the period is mostly explained by changes in structural characteristics.

3. Data

We focus on the population of hospital users in the financial years 2009/10 and 2016/17. There are two main sources of data: the Admitted Patient Care part of the Hospital Episode Statistics (APC-HES) (NHS Digital 2010; NHS Digital 2017) and the NHS Reference Costs (RC) (Department of Health 2011; NHS Improvement n.d.). APC-HES records hospital activity as *episodes*, periods under the care of one consultant. The information recorded for each episode includes: start and end dates, age and sex of the patient, type of admission and diagnoses. We can identify the Healthcare Resource Group(s) (HRG, NHS equivalent to DRGs) associated with each episode using APC-HES and the HRG RC Grouper for the respective financial year (NHS Digital 2009-10; NHS Digital 2016-17). The cost associated with each HRG is available in the RC, which report a (weighted) national average of the cost of each HRG based on the costs reported by NHS providers (Department of Health 2014). For further details regarding the costing, see Rice and Aragón (2018).

Our dependant variable is the total annual cost per patient in 2009/10 and 2016/17. We consider only episodes with a positive cost. To take into account the effect of inflation and make the costs comparable, we use the Department of Health's Pay & Price Series (Department of Health 2016) to deflate the costs in 2016/17 (i.e. express them in £ of 2009/10). Accordingly, the changes we observe are not driven by cost inflation, but reflect changes in hospital activity, such as technological change and complexity of cases.

We consider two sets of explanatory variables, those considered demand factors associated with patients, and those considered supply factors which reflect the organisation and management of care in hospitals. Demand factors include age at the beginning of the financial year (as age groups: 0-5, 5-10, 10-20, 20-30, ..., 80+), patient gender, and morbidity characteristics. The latter are based on ICD-10 diagnoses recorded for each episode. From these we create three sets of diagnostic indicators. The first set considers only the first diagnosis, the second considers all secondary diagnoses (APC-HES can record up up 20 diagnoses), and the third focuses on Ambulatory Care Sensitive Condition (ACSC; following Kasteridis et al. (2015) we identified emergency ACSC based on ICD10 codes reported in Bardsley et al. (2013)). Hospital admissions for ACSC - conditions where good quality primary care can reduce the risk of hospital admission, e.g. influenza and pneumonia, stroke and congestive heart failure - and their known temporal and spatial variation lead to the inefficient and inequitable use of secondary care services (Santos et al. 2020; Bardsley et al. 2013; Blunt 2013; Purdy et al. 2009). They are also costly, and it has been estimated that if all Local Authorities (LAs) in England performed at the level of the best performing quintile of LAs, ACSC emergency admissions would reduced by 18% with an associated reduction in health care expenditure of £238 million (Dusheiko et al. 2011). Accordingly, the first set of indicators measure the different reasons a patient is admitted to hospital (multiple admissions with the same primary diagnosis will have a single indicator) while the second set of indicators measures comorbidities the patient had during the financial year which we use to calculate the total number of comorbidities;[3] the third indicator takes value one if the patient had a ASCS diagnosis during the financial year.

[3] In 2011 HSCIC (now NHS Digital) issued a list of diagnoses that are always considered to be clinically relevant and therefore should always be recorded. This change came into effect on 1 April 2012 (see p22: Health and Social Care Information Centre (2018)). Comparing the number of comorbidities recorded in HES for 2011/12 with those recorded in 2012/13 shows no substantive differences. For example 19.95% had 1 comorbidity recorded in 2011/12 compared to 18.1% in 2012/13; 67.7% had 4 or less comorbidities recorded in 2011/12 compared with 65.5% in 2012/13; 95.8% had 10 or less recorded comorbidities in 2011/12, compared to 94.9% in 2012/13; 99.8% had 15 recorded comorbidities or less in 2011/12 compared with 99.7% in 2012/13. Overall, the policy change appears to have little effect on the overall number of comorbidities recorded.

For supply factors, we primarily use information on the type of activity as either elective or non-elective care. Elective activity can be divided into day cases (patient does not stay overnight) and inpatient (patient does stay overnight); non-elective activity can be divided into short stay (less than two days in hospital) and long stay (patients stay two or more days in hospital). We further breakdown activity into these categories. In addition we use the number of days admitted to hospital (total and elective/non-elective). In addition we include a set of dummy variables to reflect the type of hospital trust provider as either Specialist, Teaching, Acute or Other. Since it is possible for a patient to be admitted to different providers throughout the year, we use the trust status of the hospital in which the patient had most episodes.

The total population of admitted hospital care patients in 2009/10 and 2016/17 was approximately 7.1 million and 7.8 million respectively.

4. Methods

4.1. Oaxaca-Blinder Decomposition

Applying the Oaxaca-Blinder methodology (Oaxaca 1973; Blinder 1973), we decompose the difference in hospital expenditures observed between the two years 2009/10 and 20016/17, and consider its determinants due to structural changes in the characteristics of patients and care provision, and changes in the expenditure response to those characteristics. The former can be thought of as picking up changes in demographic and morbidity characteristics, and the latter changes in technology or input prices. We assume individual hospital expenditures in financial year t, Y_{it}, can be specified as:

$$Y_{it} = X_{it}'\beta_t + \epsilon_{it}, \tag{1}$$

where X_{it} includes patient demand factors (age, sex, morbidity) and hospital supply or institutional factors (length of stay, admission type) together with a constant. β is a vector of parameters and ϵ_{it} is an idiosyncratic error. The time period, either 2009/10 or 2016/17, is denoted t.

The difference between hospital costs in two different financial years can be calculated using Equation (1) evaluated at the mean for each period, assuming ϵ_{it} has mean zero $\forall t$. Assuming two periods, denoted $t = 0$ and $t = 1$, and suppressing the individual subscript for ease of notation, Equation (1) can be rearranged to show the components of the difference as (we follow the rearrangement proposed by Jann (2008)):

$$\begin{aligned}
E(Y_1) - E(Y_0) &= E(X_1'\beta_1 + \epsilon_1) - E(X_0'\beta_0 + \epsilon_0) \\
&= E(X_1)'\beta_1 - E(X_0)'\beta_0 \\
&= \underbrace{\{E(X_1) - E(X_0)\}'\beta_0}_{A} + \underbrace{E(X_0)'(\beta_1 - \beta_0)}_{B} \\
&+ \underbrace{\{E(X_1) - E(X_0)\}'(\beta_1 - \beta_0)}_{C}
\end{aligned} \tag{2}$$

Equation (2) illustrates the decomposition of the difference in the mean outcome between periods $t = 0$ and $t = 1$. The component labelled A (herein referred to as the "characteristics effect") shows the contribution due to a change in characteristics of patients (X_0 and X_1) across the two periods assuming the relationship between characteristics and expenditure are observed at time $t = 0$. Component B ("coefficients effect") is the contribution to the change in outcomes due to a change in relationship between characteristic X_0 and the outcome across the two periods, captured by the difference in coefficients ($\beta_1 - \beta_0$). The final component, C, is the effect of an interaction term between A and B. The focus of our interest lies in the relative contributions of components A and B in explaining the change in expenditures across the two periods.

The decomposition is straightforward for cardinal variables. However, for categorical variables that require a set of dummy variables to be defined to contrast against a reference category, Oaxaca and Ransom (1999) show that the standard decomposition is dependent on the chosen reference category. Yun (2005) proposes a solution based on the idea that the characteristics and coefficients effects for each outcome of the categorical variable can be computed as the average effect for that outcome when the effects are calculated by alternating the reference group. Since changing the reference category for dummy variables impacts on the constant term, this approach will also lead to a modified estimate of the constant.[4]

The results presented in section 5.2 represent the decomposition on the natural logarithm of expenditures, such that (2) can be represented as $E(lnY_1) - E(lnY_2)$. While decomposition is undertaken on a logarithmic scale, results are retransformed (exponentiated) to the original scale prior to reporting. Retransforming the data allows for a more intuitive interpretation of the decomposition effects. Since this involves a ratio of expenditures across the period it informs of the percentage increase (or decrease) in expenditure due to a change in coefficients or structural characteristics.

4.2. Decomposition across the distribution of expenditure

Decomposition techniques are based on estimating a counterfactual 'what if' outcome that would have occurred as a result of either a change in the distribution of the set of characteristics (component A), or a change in the relationship between the characteristics and the outcome (component B). Whereas the Oaxaca-Blinder approach evaluates the counterfactual at the mean of the outcome, other techniques consider the difference between groups across the full distribution of outcome (see Fortin et al. (2011) for an overview of methods). To decompose the change in HCE across its full distribution we follow the approach developed by Chernozhukov et al. (2013), who propose a decomposition method based on distributional regression (for example, see Foresi and Peracchi (1995)). Define the marginal distribution of characteristics in time period j $(j = 0, 1)$ as $F_{X_{(j)}}(x)$, and the conditional distribution of the outcome given characteristics X as $F_{Y_{(j)}}(y|x)$. The insight behind the decomposition comes from the fact that the marginal distribution of the outcome, $F_{Y_{(j)}}$, is equivalent to it's conditional distribution integrated over the distribution of covariates: $F_{Y_{(j)}}(y) = \int F_{Y_{(j)}}(y|x)dF_{X_{(j)}}(x)$. Counterfactual analysis follows directly by generalising the above, such that $F_{Y_{(j|k)}}(y) = \int F_{Y_{(j)}}(y|x)dF_{X_{(k)}}(x)$ represents the marginal distribution of the outcome in period j based on the distribution of characteristics measured in period k $(k = 0, 1)$. For example, the hypothetical distribution of HCE if the relationship between characteristics and outcomes remained as observed in time period $t = 0$, but applied to the distribution of characteristics observed in period $t = 1$ is given by: $F_{Y_{(0|1)}}(y) = \int F_{Y_{(0)}}(y|x)dF_{X_{(1)}}(x)$. The approach allows comparison between marginal and counterfactual distributions of outcomes and their decomposition. To simplify notation, we drop the parentheses such that $F_{Y_{(0|0)}}$ is the observed distribution of expenditures in period $t = 0$ and $F_{Y_{(0|1)}}$ is the counterfactual distribution of expenditures assuming patients had characteristics observed in period $t = 1$; and similarly for $F_{Y_{(1|1)}}$ and $F_{Y_{(1|0)}}$. In each (financial) year, we observe hospital costs Y and patient and hospital characteristics X. The observed distributions of hospital costs are $F_{Y_{(0|0)}}$ and $F_{Y_{(1|1)}}$, and their difference can be decomposed into differences due to differences in the coefficients (A') and to differences in characteristics (B') as:

$$F_{Y_{(1|1)}} - F_{Y_{(0|0)}} = \underbrace{\left[F_{Y_{(1|1)}} - F_{Y_{(0|1)}}\right]}_{(A')} + \underbrace{\left[F_{Y_{(0|1)}} - F_{Y_{(0|0)}}\right]}_{(B')} \tag{3}$$

[4] The analysis is performed using the Oaxaca-Blinder decomposition developed for Stata by Jann (2008) in Stata 16 (StataCorp. 2019). For categorical variables, for example sex, we use the *normalize()* option which will report the decomposition results for all categories.

Implementation of the approach requires estimation of the conditional distribution of outcomes and of the marginal distribution of characteristics. It is assumed that the conditional distributions, $F_{Y_{(j|k)}}$, are well defined where there is common support across the distribution of characteristics, X_0 and X_1. In our application this assumes that the support of both demand and supply characteristics observed in 2016/17 cover that of 2009/10, $\chi_1 \subseteq \chi_0$. The approach is computationally demanding and as such we take a random 1% sample from each year for the decomposition of the full distribution.[5]

[5] Decomposition across the full distribution was undertaken using Stata Statistical Software with the command *cdeco* developed by Chernozhukov et al. (2013) in Stata 16 (StataCorp. 2019).

Table 1: Hospital healthcare users

Expenditure	Total expenditure £Million			Expenditure per patient £				
	2009/10	2016/17		2009/10		2016/17		
	Total		%Δ	Mean	50th %tile	Mean	50th %tile	%Δ Mean
All Episodes	21,106	24,651	17	2,966	1,265	3,161	1,236	7
Elective Episodes								
All Episodes	10,233	10,843	6	2,331	1,055	2,247	986	-4
Daycases	3,805	4,919	29	1,121	741	1,230	785	10
Inpatient	6,428	5,924	-8	4,583	2,668	4,821	3,335	5
Non-Elective Episodes								
All Episodes	10,873	13,808	27	3,035	1,450	3,483	1,425	15
Short Stay	2,003	2,519	26	759	492	814	481	7
Long Stay	8,870	11,289	27	4,738	2,885	5,717	3,307	21

Activity (episodes)	Total activity Millions			Activity per patient				
	2009/10	2016/17	%Δ	2009/10		2016/17		%Δ
	Total			Mean	SD	Mean	SD	Mean
All Episodes	15.28	17.43	14	2.15	1	2.23	1	4
Elective Episodes								
All Episodes	8.22	8.76	7	1.87	1	1.82	1	-3
Daycases	5.19	6.55	26	1.53	1	1.64	1	7
Inpatient	3.04	2.21	-27	2.16	1	1.80	1	-17
Non-Elective Episodes								
All Episodes	7.05	8.67	23	1.97	1	2.19	1	11
Short Stay	3.89	4.98	28	1.47	1	1.61	1	9
Long Stay	3.17	3.68	16	1.69	1	1.87	1	10
Bed Days	34.20	34.85	2	4.81	1	4.47	0	-7
Elective	5.78	4.57	-21	1.32	0	0.95	0	-28
Non-Elective	28.42	30.28	7	7.93	2	7.64	2	-4

	2009/10		2016/17		%Δ
	Mean	SD	Mean	SD	Mean
Provider Type (prop. of episodes by type)					
Specialist	0.03	0.17	0.03	0.16	-3
Teaching	0.23	0.42	0.32	0.47	38
Acute	0.74	0.44	0.65	0.48	-12
Other	0.00	0.01	0.00	0.04	4341
Demographics & Morbidity					
Age	50.28	25.45	51.83	25.46	3
Male	0.46	0.50	0.47	0.50	1
No. of 1st diagnoses	1.29	0.65	1.33	0.70	3
No. of Comorbidities	2.05	2.14	2.96	2.69	44
ACSC diagnosis	0.16	0.37	0.17	0.38	6
Number of Observations	7,116,596		7,799,318		+9.6

5. Results

5.1. Descriptive Statistics of the Sample

5.1.1. Total expenditure and activity

Table 1 shows descriptive statistics for the two financial years of data. APC-HES reports finished episodes of hospital care, which are recorded in the financial year in which they end. Prior to analysis we excluded 549 patients whose total length of hospital stay was greater than 365 days. The number of patients admitted increased from approximately 7.1 million in 2009/10 to 7.8 million in 2016/17, an increase of 9.6%. This was associated with a 16.8% increase in the total costs of providing care from £21.1b in 2009/10 to £24.7b in 2016/17.

A breakdown in expenditure between elective and non-elective procedures is revealing. Total activity on elective care increased by around 7% across the period. Associated expenditure increased by around 6%. This was accompanied by a major shift in the treatment of patients from elective inpatient stays to daycases. Total activity shows a 26% rise in daycases, offset by a 27% fall in inpatient care. Overall, expenditure on inpatient stays fell by around 8% to £5.9b in 2016/17, while daycase expenditure rose by around 29% to £4.9b. The median cost of treating a daycase was reasonably stable across the period at around £785, while the median cost of an inpatient stay rose from £2,668 to £3,335.

In contrast, non-elective care rose substantially over the period from 7.1 to 8.7 million episodes, an approximate 23% increase. The corresponding increase in total expenditure over the period was 27% (£10.9b in 2009/10 to £13.8b in 2016/17). The increase in non-elective care expenditure rose at a faster rate than expenditure on elective care (around 21 percentage points higher), where both short stay and long stay activity increased substantially (28% and 16% respectively). While short stay activity is greater than for long stays (5m versus 3.7m in 2016/17), total expenditure on long stay activity is 4.5 times greater than for short stays (£11.3b versus £2.5b).

The total number of patients increases between 2009/10 and 2016/17 by around 9.6%, while the population in England increased by less than 6% over the same period (Office for National Statistics 2020). In terms of capacity, the total number of available beds (overnight and day-only) decreased by 10% (Overnight (NHS England n.d.[b]), Day (NHS England n.d.[a])).

5.1.2. Patient expenditure and activity

Table 1 also provides summary expenditure and activity data per patient.[6] A comparison of the median (50th %tile) with the mean indicates that the distribution of expenditures is highly skewed towards high cost patients (the mean is over twice the value of the median). While median expenditure is fairly stable over the period but showing a slight decrease (£1,265 and £1,236), the mean (£2,966 and £3,161) is suggestive of an increase in expenditure.

[6] Data broken down by elective and non-elective care use appropriate denominators. For elective care the denominator omits patients who only had non-elective admissions in the year; similarly the denominator for non-elective care omits patients who only had admissions for elective care. Similarly, we only use patients with daycase/inpatient or short/long-stay expenditure when reporting for the categories within elective and non-elective.

There was a decrease in both mean and median elective expenditure across the period which was due to a substantial shift away from inpatient stays towards day cases. Average costs for daycases are less than corresponding inpatient stays (£1,230 versus £4,821 in 2016/17). The increase in the average expenditure in daycases is greater than for inpatient stays, presumably reflecting, at the margin, a shift of more complex patients to daycases over time.

Across all non-elective episodes, average expenditure per patient increased by 15% (£3,035 in 2009/10 to £3,483 in 2016/17), while median expenditure exhibited a slight decrease. Again, this implies the observed rise in mean expenditure is due to increases in the upper part of the expenditure distribution.[7] Figure 2 provides a kernel density plot of non-elective expenditure for the two years. The main difference is an extended right-hand tail in the 2016/17 distribution compared to 2009/10.[8]

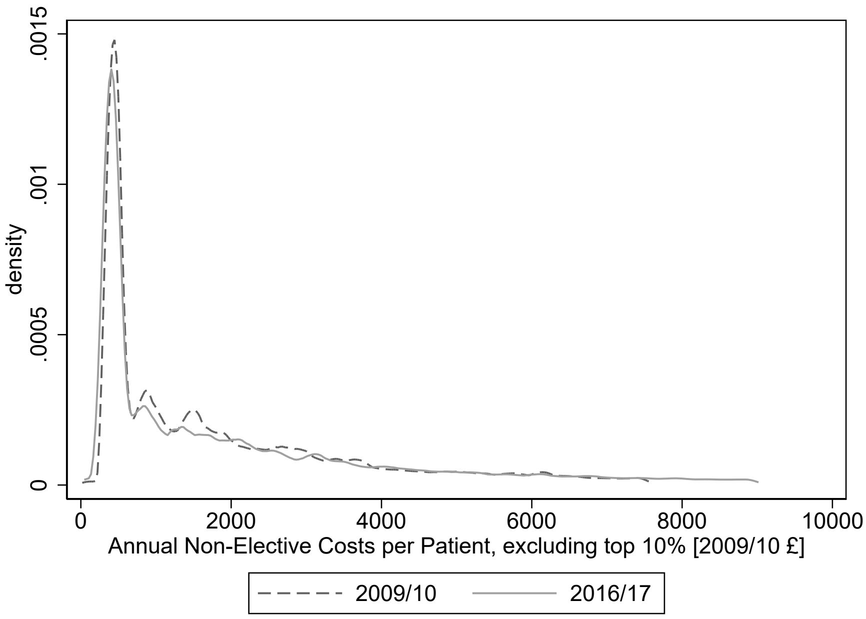

Figure 2: Kernel Density Per Patient Non-Elective Expenditure

Descriptive summaries for activity per patient reflect the general trends observed for expenditure. Overall, elective episodes per patient decreased over the period (from 1.87 to 1.82) with a pronounced decrease in inpatient care episodes (a decrease of 17% per patient). The net effect of this change was a 28% decrease in elective bed days from and average of 1.32 to 0.95 per patient. In contrast non-elective activity per patient increased by 11% to an average of 2.19 over the period, with short and long stays episodes increasing 9% and 10%, respectively. Average bed days for non-elective episodes decreased marginally by 4% but remained far greater than for elective episodes (7.64 versus 0.95 respectively in 2016/17).

[7] This is further evidenced by expenditure per patient at the 99th percentile being substantially greater in 2016/17 (£27,568, compared to a median of £1,425) than in 2009/10 (£22,133 compared to a median of £1,450). Figures not shown in the Table 1.

[8] Due to the long right-hand tails in the expenditure distribution leading to the plots lacking clarity due to the scaling required to show all data, we have omitted the top 10% of observations from each year to aid presentation.

5.1.3. Demographics, morbidity and providers

Table 2 reports summary activity statistics by age, gender, morbidity and type of provider separately for elective and non-elective care. The average age of patients increased for both forms of care by about 18 months, and is three to four years higher for elective compared to non-elective care. The corresponding increase in life expectancy over the period was less than a year for both men and women (see Office for National Statistics (2019a)). The proportion of men is slightly higher for non-elective care than elective care. There was a slight increase in the number of first diagnoses (reflecting more episodes of care per patient) which was more notable for non-elective than elective care. However, there was a substantial rise in the average number of reported comorbidities (from 2.64 (1.42) to 3.68 (2.19) for non-elective (elective) care) suggesting increased frailty in the population. The proportion of patients with an ACSC diagnosis was greater in non-elective than in elective care; the difference was slightly larger in 2016/17 (25% and 9% respectively) than in 2009/10 (23% and 9% respectively). In total there were 4.8m elective patients in 2016/17, a rise of 9.9% on 2009/10. This is greater than the corresponding number of non-elective patients (4m in 2016/17), but the rise from 2009/10 in non-elective patients is slightly larger at 10.7%.

There was a shift away from acute hospital care settings towards teaching providers across the period.[9] In 2016/17 teaching hospitals admitted nearly a third of all patients with acute hospitals admitting two-thirds. This compares to respectively one quarter and three quarters in 2009/10. From Table 2 we see similar proportions of elective and non-elective admissions in teaching and acute hospitals.

Table 2: Elective / Non-Elective healthcare users

	2009/10		2016/17		%Δ
	Mean	SD	Mean	SD	Mean
	Elective healthcare				
Activity (episodes per patient)					
Provider Type (prop. of episodes by type)					
Specialist	0.04	0.19	0.04	0.19	1
Teaching	0.24	0.43	0.32	0.47	33
Acute	0.72	0.45	0.64	0.48	-11
Other	0.00	0.01	0.00	0.04	-
Demographics & Morbidity					
Age	52.40	22.28	54.00	22.05	3
Male	0.46	0.50	0.47	0.50	2
No. of 1st diagnoses	1.15	0.41	1.16	0.43	1
No. of Comorbidities	1.42	1.51	2.19	1.91	53
ACSC diagnosis	0.09	0.28	0.09	0.28	-
Number of Observations	4,389,195		4,825,203		9.9%
	Non-Elective Episodes				
Provider Type (prop. of episodes by type)					
Specialist	0.02	0.13	0.02	0.12	-17
Teaching	0.22	0.42	0.32	0.47	44
Acute	0.76	0.43	0.66	0.47	-13
Other	0.00	0.00	0.00	0.04	-
Demographics & Morbidity					
Age	49.18	28.46	50.61	28.61	3
Male	0.48	0.50	0.48	0.50	0
No. of 1st diagnoses	1.28	0.63	1.31	0.70	3
No. of Comorbidities	2.64	2.36	3.68	2.98	39
ACSC diagnosis	0.23	0.42	0.25	0.43	9
Number of Observations	3,582,135		3,964,282		10.7%

[9] Other Providers consist largely of non-acute trusts. In 2009/10 these included mental health (MH) trusts and primary care organisations (PCOs). In 2016/17, these included MH Trusts and community trusts together with a merger in October 2014 between Ealing Hospital NHS Trust and The North West London Hospitals NHS Trust, which created one of the largest integrated acute and community care trusts in the country.

5.2. Decomposition at the mean of expenditures

This section considers the observed changes in expenditure by applying decomposition techniques outlined in Section 4. Being regression based, the approach allows us to condition on covariates when considering the decomposition of a particular variable. Given that the main driver of the rise in admitted patient expenditure has been non-elective care we focus the decomposition analysis on this area of activity.

Table 3 presents results of the Oaxaca decomposition of the change in average non-elective patient expenditure. Due to the skewed nature of the expenditure data, a logarithmic transformation is applied prior to analysis. As a consequence, and in contrast to the arithmetic means presented in Tables 1 and 2, the results for expenditure per patient represent geometric means.[10] The estimated difference in expenditure (and its decomposition) is expressed as a ratio. The top panel of the table shows that the geometric mean of non-elective inpatient expenditure per patient in 2009/10 was £1,510 which increased slightly to £1,523 in 2016/17. This represents an increase of 0.9% (Difference = 1.009).[11]

The decomposition of the *difference* in average per patient expenditure is presented as an effect due to a change in the distribution of explanatory variables (Characteristics), an effect due to a change in the relationship between characteristics and expenditure (Coefficients), and an interaction term. To conserve space, we report decomposition results for activity and the categories of morbidity which display the largest effects in terms of a change in either covariate distribution or a change in coefficients. The categories used for morbidity are ICD chapters described in Table A.1 of the appendix. The second and third columns display separately for 2009/10 and 2016/17 coefficients from regressions of log expenditure on the set of covariates. These regressions are able to explain around 70% of observed variation in expenditure at the patient level.

Columns four to six of Table 3 present the results of the decomposition analysis. The second panel of the table summarises the contribution of characteristics, coefficients and their interaction. The coefficient for the impact of a change in characteristics is 1.063. This implies that expected non-elective expenditure in 2009/10, if demand and supply factors had the characteristics of those observed in 2016/17, would have been 6.3% higher than that observed. Accordingly, the shift in the distribution of patient and hospital level characteristics over the period has contributed to increased expenditures. Conversely, applying the coefficients for the relationship between covariates and expenditure estimated for 2016/17 to the characteristics observed in 2009/10, would have led to an expected 8.7% ($100\% \times (1 - 0.913)$) decrease in average expenditure in 2009/10. Accordingly, on average, treatment costs in 2016/17 for a given non-elective inpatient episode became cheaper compared to 2009/10, implying gains in efficiency. In summary, changes to the distribution of patient characteristics over the seven year period increased average non-elective expenditures, but these have been offset by gains in efficiency in treating conditions. A positive interaction between characteristics and coefficients led to a further increase in average expenditure of around 4%. The combined effects explain the observed 0.9% growth in average per patient expenditure between 2009/10 and 2016/17. We explore further below the individual contributing factors to these findings.

[10] The geometric mean indicates the central tendency by calculating the n^{th} root of the product of n numbers. This differs from the arithmetic mean which calculates the average of a sum of n numbers. Unless all numbers are equivalent, in which case the two means coincide, the geometric mean is always less than the arithmetic mean.

[11] This is a smaller increase than that observed in Table 1 due to the arithmetic means being overly influenced by the skewness in the expenditure data. The geometric means presented in Table 3 are less influenced by skewness since they operate on a logarithmic scale.

Table 3: Blinder-Oaxaca Decomposition of Non-Elective Hospital Costs between 2009/10 and 2016/17

	2009/10	2016/17	Difference - % increase		
Average Expenditure †	1,510	1,523	1,009		
	Regression coefs.		Decomposition (as ratio)		
	2009/10	2016/17	Characteristics	Coefficients	Interaction
Decomposition (as ratio)			1.0628***	0.9134***	1.0391***
			(0.0008)	(0.0005)	(0.0004)
Episodes - total effect			1.0154***	0.9620***	0.9996***
			(0.0005)	(0.0007)	(0.0001)
Short	-0.0430***	-0.0293***	0.9927***	1.0149***	1.0023***
	(0.0003)	(0.0003)	(0.0001)	(0.0005)	(0.0001)
Long	0.4969***	0.4363***	1.0229***	0.9478***	0.9972***
	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0001)
Bed Days	0.0105***	0.0087***	0.9969***	0.9859***	1.0005***
	(0.0000)	(0.0000)	(0.0001)	(0.0003)	(0.0000)
First Diagnosis - total effect			0.9869***	0.9887***	1.0079***
			(0.0002)	(0.0014)	(0.0002)
ICD10 - Ch5	-0.8223***	0.0040	0.9870***	1.0042***	1.0133***
	(0.0046)	(0.0025)	(0.0001)	(0.0000)	(0.0001)
ICD10 - Ch9	0.2685***	0.3169***	0.9989***	1.0065***	0.9998***
	(0.0012)	(0.0013)	(0.0001)	(0.0002)	(0.0000)
ICD10 - Ch10	0.1177***	0.0618***	1.0045***	0.9922***	0.9979***
	(0.0013)	(0.0013)	(0.0001)	(0.0003)	(0.0001)
ICD10 - Ch11	0.2512***	0.3382***	0.9978***	1.0112***	0.9992***
	(0.0012)	(0.0013)	(0.0001)	(0.0002)	(0.0000)
ICD10 - Ch18	-0.0783***	-0.1495***	1.0023***	0.9808***	1.0021***
	(0.0010)	(0.0010)	(0.0000)	(0.0004)	(0.0000)
ICD10 - Ch19	0.2615***	0.2774***	0.9938***	1.0032***	0.9996***
	(0.0011)	(0.0012)	(0.0001)	(0.0003)	(0.0000)
Number of Comorbidities	0.0530***	0.0883***	1.0567***	1.0978***	1.0374***
	(0.0002)	(0.0002)	(0.0003)	(0.0008)	(0.0003)
ACSC diagnosis	-0.0430***	-0.0106***	0.9992***	1.0075***	1.0006***
	(0.0009)	(0.0010)	(0.0000)	(0.0003)	(0.0000)
Constant	6.5603***	6.6111***		0.8466***	
	(0.0027)	(0.0031)		(0.0141)	
Adjusted R-squared	0.7065	0.6863			
N	3,582,135	3,964,282		7,546,417	

† Predicted (geometric) average expenditure (per patient).
Standard errors in parenthesis. ***, **, * represent 1%, 5% and 10% significance, respectively.
Baseline for regression coefficients for ICD chapters is ICD20; baseline provider status is Specialist; baseline for Age is 0-5 years.

The constant term at the bottom of the table reports the change in average expenditure per patient that cannot be explained by the set of demand and supply factors included in the model (that is, when all supply- and demand-side characteristics are set to zero). While overall (geometric) mean expenditure per patient increased between 2009/10 and 2016/17 by 0.9%, the unexplained component contributes with a decrease of 15%. While we can only speculate of the underlying causes for the unexplained decrease, supply-side factors such as efficiency gains through technological change and improved management of patients are likely to dominate, although it will also reflect unobservable demand-side factors. To the extent that these factors are unmeasured, they will be captured by the constant term.

On the supply-side, adjusting the mix of episode types (short and long stay) in 2009/10 to the configuration observed in 2016/17 contributed to raising average expenditures by around 1.5%. This was driven by a shift away from short stays towards long stay care across the period. However, this was offset by an expected 3.8% decrease in average expenditure due to a coefficient effect. In turn this was driven by a substantial (around 5.2%) decrease in average treatment costs for long stay patients offset by an increase (of around 1.5%) in short stay patient costs.

On the demand-side, we focus on the effects of morbidity characteristics. While the contribution of ICD chapters for first diagnosis are generally small, there are a few chapters where either the relative incidence of these conditions changed and/or per patient costs for treatment changed over the period. Overall, if the mix of ICD chapter diagnoses in 2009/10 had the distribution observed in 2016/17, then overall average expenditures would have been expected to be approximately 1.3% less than observed. Similarly if the expenditure response to morbidity in 2009/10 was that estimated for 2016/17 expected costs would have been lower by around 1.1%. While these effects are offset slightly by an interaction between characteristics and coefficient effects (of approximately 0.8%), overall a change in the distribution of primary diagnosis together with associated treatment costs appears to have led to decreases in average expenditure over time. The table displays more detailed results for individual ICD chapters which exhibit effects for either coefficient or characteristics of 0.5% or more.

By far the largest effect of all of the covariates within the decomposition analysis is that attached to the number of comorbidities. Average expected expenditure in 2009/10 would have been 5.7% greater than observed if the comorbidity profile of patients looked the same as seen in 2016/17. Expected expenditure would have been a further 10% greater if the treatment response to comorbidities in 2009/10 had taken the form of the response in 2016/17. This joint effect is increased further by a positive interaction term (of 3.7%). The substantial increase in comorbidities across the period of observation has contributed hugely to average per patient non-elective expenditures.

The ACSC diagnosis indicator presents results that partially offset each other. Average costs in 2009/10 would have been very slightly lower (-0.1%) had the proportion of patients with an ACSC diagnosis been that observed for 2016/17. However, the cost of treatment would have been slightly higher (0.7%) if the relationship between ACSC diagnosis and expenditure in 2009/10 had been that observed for 2016/17. Accordingly, conditional on other characteristics, overall the impact of ACSCs across the period was to increase expenditure slightly.

Figure 3 summarizes the full set of results for the model shown in Table 3. For each set of variables the point estimate of the decomposition into characteristics and coefficients is displayed together with respective confidence intervals. The vertical line presented at unity indicates the null of no effect, and estimates with confidence interval that dissect this line are not statistically significantly different to the null effect. Points to the right of the vertical line represent positive contributions to expenditure changes, points to the left represent reductions to expenditure. The impact of comorbidities for both characteristics and coefficients relative to other covariates is clearly shown. Both effects are positioned to the right and are estimated with precision (small confidence intervals).

5.3. Decomposition across the distribution of expenditures

This section reports results based on the decomposition method of Chernozhukov et al. (2013) using an 1% random sample from the data used for the Oaxaca Decomposition. To simplify the presentation, Table 4 reports the difference in observed outcomes and their summary decomposition at deciles of the

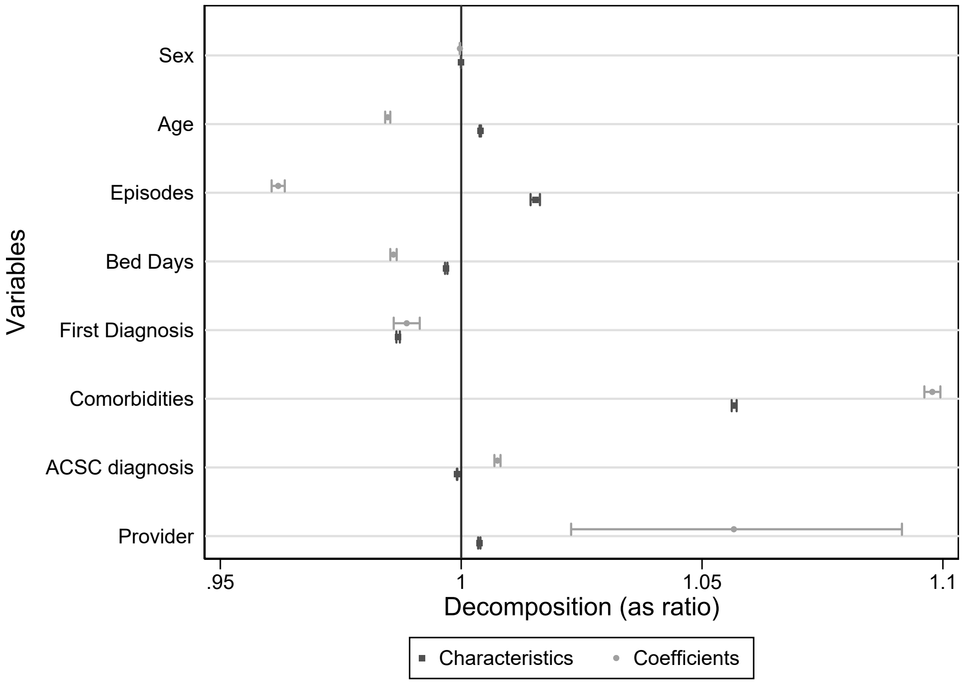

Figure 3: Summary of Oaxaca Decomposition Results

distribution (we also include the 95th and 99th percentile).[12] These are calculated on a log scale. A full breakdown of the results estimated at each percentile is presented in Figure 4. A positive (negative) effect indicates that the contribution of a characteristic or coefficient acted to increase (decrease) average expenditure at that decile over the period 2009/10 to 2016/17.

The first five deciles of column 2 of Table 4 show an overall negative change in expenditures (a decrease in expenditure from 2009/10 to 2016/17). The change is then positive and increasing in magnitude thereafter. Larger increases are observed at the top of the expenditure distribution. That is, expensive to treat patients raised expenditures disproportionately more than less expensive patients. Estimated effects are significantly different from zero below the 48th percentile and above the 63rd percentile. Columns 3 and 4 show the decomposition results for the effect of a change in characteristics and the effect for a change in coefficients. The former are positive and statistically significant from the 33rd percentile upwards, implying their contribution acted to increase average expenditures. The estimates for the effects of a change in coefficients are all negative and statistically significantly different from zero across the full distribution.

In general the changes in expenditure across the quantiles are driven by changes in coefficients at the bottom end of the distribution but are dominated by changes in characteristics in the top half of the distribution. At the very top of the distribution estimated effects from both characteristics and coefficients are large and opposing in magnitude. At the 95th (99th) percentile the overall increase in non-elective expenditure of 21.9% (51.5%), can be decomposed into the contribution of a change in characteristics of 34.3% (76.0%) and a change in coefficients of -12.4% (-24.5%). While, on average, treatment costs decreased across the full distribution of expenditures, these have been offset by an increasing shift

[12] The results report the change in overall non-elective expenditure and its decomposition and does not break these down by individual covariate contributions as in the Oaxaca decomposition of Section 5.2.

Table 4: Counterfactual Decomposition of Differences in Distributions - Log(Hospital Costs) between 2009/10 and 2016/17

Decile	Differences between the observable distributions	Effects of characteristics	Effects of coefficients
10	-0.096	0.009	-0.105
	[-0.106, -0.086]	[0.003, 0.0153]	[-0.113, -0.097]
20	-0.077	0.006	-0.083
	[-0.096, -0.057]	[-0.004, 0.017]	[-0.098, -0.068]
30	-0.083	0.009	-0.092
	[-0.105, -0.060]	[-0.004, 0.022]	[-0.108, -0.076]
40	-0.059	0.020	-0.079
	[-0.079, -0.038]	[0.009, 0.032]	[-0.093, -0.065]
50	-0.012	0.029	-0.041
	[-0.034, 0.010]	[0.016, 0.043]	[-0.054, -0.028]
60	0.014	0.040	-0.026
	[-0.010, 0.038]	[0.025, 0.056]	[-0.039, -0.013]
70	0.052	0.066	-0.014
	[0.027, 0.078]	[0.049, 0.083]	[-0.028, 0.0001]
80	0.083	0.112	-0.027
	[0.054, 0.113]	[0.089, 0.135]	[-0.046, -0.012]
90	0.152	0.225	-0.073
	[0.115, 0.189]	[0.186, 0.263]	[-0.099, -0.046]
95	0.219	0.343	-0.124
	[0.177, 0.262]	[0.280, 0.406]	[-0.169, -0.078]
99	0.515	0.760	-0.245
	[0.391, 0.638]	[0.583, 0.937]	[-0.356, -0.134]
N 2009/10		35,821	
N 2016/17		39,643	

Pointwise Confidence Interval in brackets.

towards a higher proportion of what appear to be more complex and expensive to treat patients. This is particularly relevant at the top end of the distribution.

Figure 4 plots the overall change in expenditures together with the effects of coefficients and characteristics across the full expenditure distribution. Up to 50th percentile, the plotted lines for the observed change in expenditures and the coefficients effect overlap emphasizing the strong contribution of coefficients to the overall change in this part of the distribution. In contrast, in the top half of the distribution the change in expenditure is more closely matched to the contribution in the change in characteristics. It is likely that the effect was driven by demand-side characteristics, and in particular increased complexity of cases observed through increased numbers of comorbidities.

To better understand the decomposition results across the full distribution, Table 5 summaries the differences in means between 2009/10 and 2016/17 for the key covariates broken down into the bottom 10%, the middle (10th to 90th percentile), and the top 10% of the expenditure distribution. This illustrates the large increase in expenditure observed at the top end of the distribution (£3,116) compared to other parts of the distribution (-£59 in the bottom 10% and £177 in the middle of the distribution). This was accompanied by an increase in the average number of episodes at the top of the distribution. The change in the number of comorbidities and in the number of first diagnoses increase across the two periods to a greater extent at the top of the expenditure distribution than in other areas of the distribution. Again, this emphasises the role of co-morbidity in driving expenditure increases. The proportion of patients with an ACSC diagnosis increased slightly between 2009/10 and 2016/17, with the increase being greater in the top 10% of the expenditure distribution. While the average age of patients treated decreased in the lower part of the expenditure distribution, it increases in the middle and, to a lesser extent, the top of the distribution.

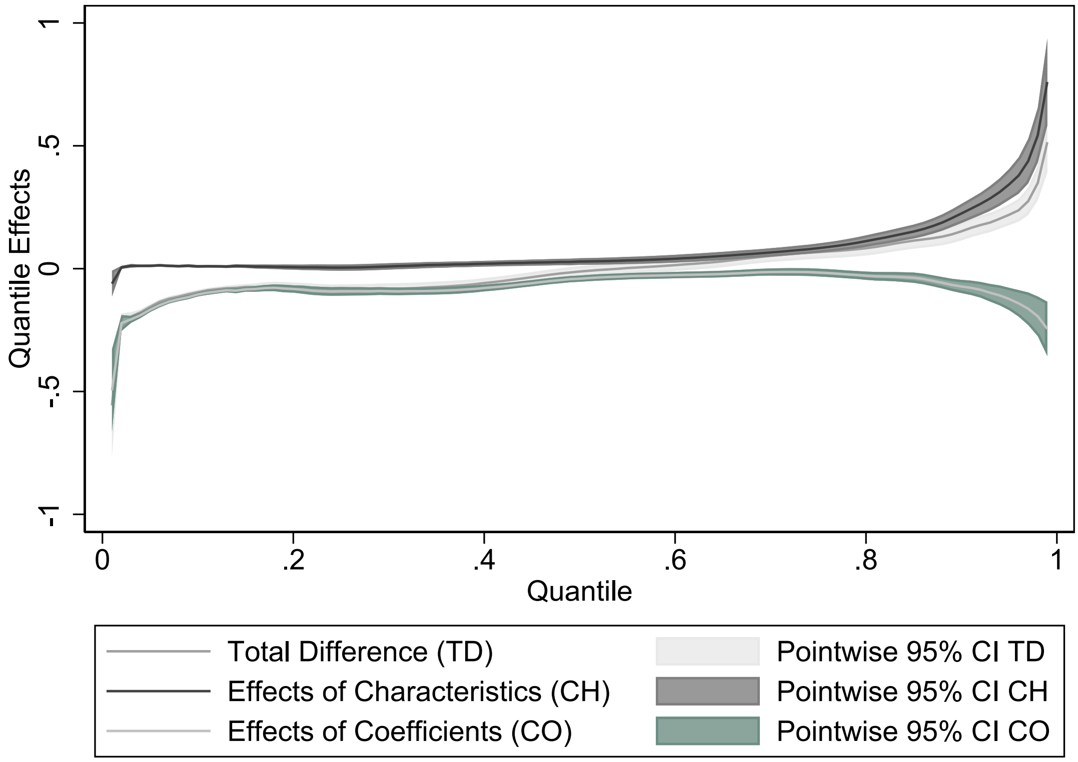

Figure 4: Counterfactual Decomposition of Differences in Distributions - Log(Hospital Costs) between 2009/10 and 2016/17

Table 5: Non-Electives: Differences in means across the distribution of expenditures

	Bottom 10%		Middle [10th - 90th pctile]		Top 10%	
	Diff.Mean	StdErr	Diff.Mean	StdErr	Diff.Mean	StdErr
Non-Elective Cost	-59	0.11	177	1.57	3,116	20.27
Non-Elective Episodes	0.00	0.00	0.15	0.00	1.00	0.01
Short	-0.02	0.00	0.16	0.00	0.50	0.01
Long	0.02	0.00	-0.01	0.00	0.50	0.01
Non-Elective LoS	0.01	0.01	-0.33	0.01	0.37	0.08
Provider Type						
Specialist	0.00	0.00	0.00	0.00	0.00	0.00
Teaching	0.13	0.00	0.10	0.00	0.08	0.00
Acute	-0.13	0.00	-0.09	0.00	-0.08	0.00
Other	0.00	0.00	0.00	0.00	0.00	0.00
Demographics						
Age	-4.41	0.05	2.22	0.02	1.15	0.05
Male	0.00	0.00	0.00	0.00	0.02	0.00
Diagnoses (ICD10 Chapters)						
First Diagnoses	0.00	0.00	0.03	0.00	0.18	0.00
Comorbidities	0.19	0.00	1.01	0.00	2.16	0.01
ACSC diagnosis	0.03	0.00	0.01	0.00	0.07	0.00
Obs 2009/10	369,176		2,854,746		358,213	
Obs 2016/17	405,189		3,162,665		396,428	

5.4. Age and morbidity

Table 6 provides a breakdown of the percentage of patients by type of care, age group and morbidity. The top panel clearly shows that the proportion of very old patients (80+) was greater for non-elective care (18.7% in 2016/17) than for elective care (9.8% in 2016/17). For age groups from 50 years to 80 years there was a greater share for elective care than non-elective care. Note that the proportion of patients in age group 50 years and upwards have all increased over time irrespective of care setting. Proportionately there has not been a greater shift towards more elderly patients seen in non-elective settings compared to elective settings. The second panel of the table provides a breakdown of the average number of comorbidities by age group and type of care. The largest numbers of comorbidities were observed for non-elective care and these increased with age. In the 80+ years age group the average number of comorbidities was at least twice as large for non-elective care (average of 6.2 in 2016/17) compared to elective care (average of 3.1 in 2016/17). The final panel reports the percentage of patients by number of comorbidities. For both types of care there has been a substantial increase in the proportion of patients with 4 or more comorbidities. In particular, the proportion with 5 or more comorbidities in non-elective care settings is nearly three times that for elective care (33% versus 12% in 2016/17).

Table 6: Age and morbidity between 2009/10 and 2016/17

	All			Electives			Non-electives		
	2009/ 2010	2016/ 2017	Diff. (%)	2009/ 2010	2016/ 2017	Diff. (%)	2009/ 2010	2016/ 2017	Diff. (%)
Percentage of patients by Age									
50 - 60	12.3	14.3	16	14.8	17.4	18	9.5	10.4	10
60 - 70	14.8	15.2	3	18.2	18.6	3	11.3	11.7	4
70 - 80	14.4	15.2	5	16.1	17.2	7	13.7	14.0	2
80+	12.4	13.5	8	9.0	9.8	8	17.2	18.7	8
Average comorbidities by Age									
50 - 60	1.92	2.62	36	1.43	2.04	42	2.68	3.59	34
60 - 70	2.33	3.30	41	1.74	2.56	47	3.24	4.39	36
70 - 80	2.98	4.04	36	2.04	2.92	43	3.89	5.20	34
80+	3.81	5.34	40	2.04	3.07	51	4.49	6.19	38
Percentage of patients by number of comorbidities									
0	26.1	16.2	-38	33.2	20.0	-40	17.6	11.4	-35
1	25.1	20.2	-19	28.8	23.8	-17	21.7	16.2	-25
2	17.2	17.1	0	17.7	19.7	11	17.8	15.2	-15
3	11.7	13.5	15	10.6	14.8	40	13.8	13.2	-5
4	7.5	9.9	33	5.4	9.8	82	10.0	11.0	10
5+	12.5	23.1	85	4.4	12.0	176	19.1	33.0	73

Observations: 2009/10: All 7,116,596, Electives 4,389,195, Non-electives 3,582,135; 2016/17: All 7,799,318, Electives 4,825,203, Non-electives: 3,964,282

5.5. Morbidity, episodes of care and expenditure

Table 7 presents summary statistics for the average number of episodes and expenditure by number of comorbidities for non-elective patients. Across the period, there was a substantial increase (91%) in patients with high dimensional comorbidities (5+). However, the average number of episodes of care for all categories of comorbidities decreased as did average expenditure per patient, even in the high-dimensional group of patients. Overall expenditure increased substantially due to there being many more individuals admitted with multiple comorbidities, and relatively fewer with only 0, 1 or 2 comorbidities.

Table 7: Morbidity, episodes and expenditure of non-elective care

No. of comorbi -dities	No. of patients 1,000		Average episodes		Average expenditure £†		Total expenditure £m†	
	2009/ 2010	2016/ 2017	2009/ 2010	2016/ 2017	2009/ 2010	2016/ 2017	2009/ 2010	2016/ 2017
0	628	451	1.16	1.16	993	864	624	390
1	777	643	1.30	1.26	1,361	1,115	1,058	717
2	637	601	1.52	1.42	1,876	1,459	1,195	877
3	497	525	1.82	1.64	2,613	1,941	1,298	1,018
4	358	436	2.23	1.92	3,617	2,590	1,295	1,131
5+	684	1,308	3.83	3.66	7,892	7,398	5,402	9,674
Total	3,582	3,964	1.97	2.19	3,035	3,483	10,873	13,808

†in 2009/10 prices

6. Summary and discussion

This paper considers the detailed breakdown of hospital admitted care expenditures across the period 2009/10 to 2016/17. Decomposition techniques are used to unpick the observed growth in expenditure into components due to a change in the distribution of characteristics and due to a change in the impact of such characteristics on expenditures. We undertake this analysis on the population of hospital admitted care patients in each of the two years. The overall growth in expenditure was £3.5b with a corresponding growth in patients of approximately 700,000; an average of 100,000 per year and an increase of 9.6% on 2009/10. Growth in admitted patients was accompanied by an increase of 2.15 million episodes (14% increase on 2009/10). This is above the expected increase based on average episodes per patient in 2016/17 ($2.23 \times 700,000 = 1.56m$), pointing towards patients presenting with increased complexity of health care needs.

Non-elective care accounted for 75% of the increase in total episodes, and 83% of the total expenditure increase between 2009/10 and 2016/17. Increased non-elective activity was observed across both short stays (1.09 m episodes or 28% increase on 2009/10) and long stays (0.51 m or 16% increase on 2009/10). Long stay cases, however, contributed £2,419 m (82%) to the observed total non-elective care expenditure increase of £2,935 m.

At a patient level, the main contributing demand-side factor to the observed increase in non-elective care was an increasing complexity of patients. The proportion of patients presenting with multiple comorbidities (5+) rose dramatically across the period such that by 2016/17, 33% of non-elective patients had five or more comorbidities. This contrasts with 19% in 2009/10. These were predominantly located within older patients (70-80 and 80+ years age groups), but average comorbidities in age groups 50 to 60 and 60 to 70 also increased to 2016/17. Coupled with a slight increase in the proportions of patients admitted in these age groups, the net effect was to drive up expenditures at the top of the expenditure distribution, particularly the upper 10%. While the proportion of older more complex patients has risen, decomposition analysis suggests that the per patient costs of treatment across all deciles of the expenditure distribution decreased - that is more efficient treatment for a given level of complexity appears evident in 2016/17 compared to 2009/10. These efficiency gains are, however, far outweighed by the increasing proportions of complex comorbid patients admitted to non-elective care.

The findings suggest that future research should focus predominantly on two areas. First, understanding the reasons for the observed increased use of non-elective patient admitted care. While changing patient needs and preferences over type of access to secondary may have contributed to this rise, structural changes in the delivery of primary care services and referral mechanisms are also likely to play a significant role. These might also extend to the level and quality of community and social care services that are commissioned and provided locally. It is notable that per capita spending on health care in England exhibited a period of level funding followed by growth between 2009/10 and 2015/16. Growth over this period, however, was lower than that observed across the previous five years (see Figure 1). A continuation of pressure on services due to rising demand during this period of constrained growth may well have contributed to the observed increase in unplanned non-elective care. Secondly, research on multiple co-morbidity is urgently required. Such patients have greater contact with admitted care services and place a heavy burden on health care expenditures (for example, see Marengoni et al. (2011)). As populations age, health care services can expect a higher proportion of patients with complex needs due to the accumulation of multiple conditions. A focus on multimorbidity as a research agenda has gained traction (Academy of Medical Sciences 2018; Whitty et al. 2020). Research might usefully take three forms. Understanding the reasons behind the observed increase in multi-comorbidity over the past decade, particularly in the very elderly population, is clearly required. Related to this is a need to classify multiple comorbidity into useful clusters of conditions that are meaningful in terms of their health care resource implications. Current attempts at describing multimorbidity has tended to view these as clusters or groups of conditions identified through population prevalence data and using methods such as cluster analysis or latent class models (Ng et al. 2018). Given the impact of multimorbidity on health care expenditures, a more productive avenue of research would be to consider clusters of conditions defined not on population prevalence, but on the costs they generate in care settings (see Stokes et al. (2021)). Identifying and understanding commonly occurring and expensive to treat clusters may then better inform treatment pathways that may reduce expenditures without lowering quality of outcomes. This may also extend to identifying better preventative (for example, see Katikireddi et al. (2017)) and maintenance programmes in primary care to help mitigate the deterioration of patients to the point that they end up as emergency care and non-elective admissions (Roland and Abel 2012). Finally, the decomposition analysis fails to explain 15% of the rise in expenditure over the study period which is attributed to the constant term. This points towards important unobserved factors that have led to a significant decrease in expenditure. Understanding the underlying mechanisms that explain this effect requires richer data on both supply-side and demand-side characteristics.

The results of this analysis need to be placed within the context of broader economic constraints within which the NHS operates. Decisions to access and consume health care resources is not simply based on the needs of patients. Supply-side decisions about the allocation of resources across disease groups and individuals are implicitly made within a budget constraint. Accordingly the level of overall sickness or ill-health within the population is not the only influence on aggregate HCE in a publicly funded system. Political preferences and economic growth are both major determinants of funding levels and the broader organisation of health care provision (see for example, Getzen (2001)). While comparing the determinants of expenditure across periods is not straightforward in any dynamic system, the decomposition analysis employed helps elucidate effects due to changes in the distribution of drivers, both demand and supply, together with changes in how a given characteristic, such as a given condition, is treated. The techniques further allow investigation of where in the distribution of expenditures these effects are most prominent and where expenditure growth has been most notable.

References

Academy of Medical Sciences (2018). *Multimorbidity: a priority for global health research*. Tech. rep. Academy of Medical Sciences.

Bardsley, M., I. Blunt, S. Davies and J. Dixon (2013). 'Is secondary preventive care improving? Observational study of 10-year trends in emergency admissions for conditions amenable to ambulatory care'. *BMJ Open*, 3: DOI: 10.1136/bmjopen-2012-002007.

Blinder, A. S. (1973). 'Wage Discrimination: Reduced Form and Structural Estimates'. *The Journal of Human Resources*, 8: 436–455. ISSN: 0022166X. URL: http://www.jstor.org/stable/144855.

Blunt, T. (2013). *Focus on preventable admissions: Trends in emergency admissions for ambulatory care sensitive conditions, 2001 to 2013*. Tech. rep. The Health Foundation. URL: https://www.health.org.uk/publications/qualitywatch-focus-on-preventable-admissions.

Charlesworth, A., L. Hawkins and L. Marshall (Feb. 2014). *NHS payment reform: lessons from the past and directions for the future*. Research report. Nuffield Trust. URL: https://www.nuffieldtrust.org.uk/research/nhs-payment-reform-lessons-from-the-past-and-directions-for-the-future.

Chernozhukov, V., I. Fernandez-Val and B. Melly (Nov. 2012). *Inference on Counterfactual Distributions*. URL: http://www.mit.edu/~vchern/papers/counterfactual_2012Nov1.pdf.

Chernozhukov, V., I. Fernández-Val and B. Melly (2013). 'Inference on Counterfactual Distributions'. *Econometrica*, 81: Stata commands: https://sites.google.com/site/blaisemelly/computer-programs/inference-on-counterfactual-distributions, 2205–2268. ISSN: 1468-0262. DOI: 10.3982/ECTA10582. URL: http://dx.doi.org/10.3982/ECTA10582.

de Meijer, C., O. O'Donnell, M. Koopmanschap and E. van Doorslaer (2013). 'Health expenditure growth: Looking beyond the average through decomposition of the full distribution'. *Journal of Health Economics*, 32: 88–105. ISSN: 0167-6296. DOI: http://dx.doi.org/10.1016/j.jhealeco.2012.10.009. URL: http://www.sciencedirect.com/science/article/pii/S0167629612001701.

Department of Health (2011). *NHS reference costs 2009-10*. URL: https://www.gov.uk/government/publications/nhs-reference-costs-2009-2010.

— (2014). *NHS reference costs*. URL: https://www.gov.uk/government/collections/nhs-reference-costs.

— (2016). *HCHS Pay & Price Inflation*. URL: http://www.info.doh.gov.uk/doh/finman.nsf/af3d43e36a4c8f8500256722005b77f8/360a47827991d10a80258036002d8d9f/$FILE/2015.16%20Pay%20&%20Price%20series.xlsx.

Dormont, B., M. Grignon and H. Huber (2006). 'Health expenditure growth: reassessing the threat of ageing'. *Health Economics*, 15: 947–963. ISSN: 1099-1050. DOI: 10.1002/hec.1165. URL: http://dx.doi.org/10.1002/hec.1165.

Dusheiko, M., T. Doran, H. Gravelle, C. Fullwood and M. Roland (2011). 'Does Higher Quality of Diabetes Management in Family Practice Reduce Unplanned Hospital Admissions?' *Health Services Research*, 46: 27–46.

Foresi, S. and F. Peracchi (1995). 'The Conditional Distribution of Excess Returns: An Empirical Analysis'. *Journal of the American Statistical Association*, 90: 451–466. ISSN: 01621459. URL: http://www.jstor.org/stable/2291056.

Fortin, N., T. Lemieux and S. Firpo (2011). 'Chapter 1 - Decomposition Methods in Economics'. In: *Handbook of Labor Economics*. Ed. by O. Ashenfelter and D. Card. Vol. 4, Part A. Handbook of Labor Economics. Elsevier, 1–102. DOI: 10.1016/S0169-7218(11)00407-2. URL: http://www.sciencedirect.com/science/article/pii/S0169721811004072.

Getzen, T. E. (2001). 'Aging and health care expenditures: A comment on Zweifel, Felder and Meiers'. *Health Economics*, 10: 175–177. ISSN: 1099-1050. DOI: 10.1002/hec.593. URL: http://dx.doi.org/10.1002/hec.593.

Harker, R. (2019). 'NHS Funding and Expenditure'. *House of Commons Library*, Briefing Paper, CBP0724:

Health and Social Care Information Centre (2018). *Coding Clinic*. Tech. rep. Health and Social Care Information Centre. URL: https://hscic.kahootz.com/gf2.ti/f/762498/35472645.1/PDF/-/Coding_Clinic_V7.0.pdf.

HM Treasury (2010-2017). *Public Expenditure Statistical Analyses (PESA)*. URL: https://www.gov.uk/government/collections/public-expenditure-statistical-analyses-pesa.

Jann, B. (2008). 'The Blinder-Oaxaca decomposition for linear regression models'. *Stata Journal*, 8: 453–479(27). URL: http://www.stata-journal.com/article.html?article=st0151.

Kasteridis, P., A. R. Mason, M. K. Goddard, R. Jacobs, R. Santos and G. McGonigal (Mar. 2015). 'The Influence of Primary Care Quality on Hospital Admissions for People with Dementia in England: A Regression Analysis'. *PLOS ONE*, 10: 1–14. DOI: 10.1371/journal.pone.0121506. URL: https://doi.org/10.1371/journal.pone.0121506.

Katikireddi, S. V., K. Skivington, A. H. Leyland and M. S (2017). 'The contribution of risk factors to socioeconomic inequalities in multimorbidity across the lifecourse: a longitudinal analysis of the Twenty-07 cohort'. *BMC Medicine*, 15: DOI: 10.1186/s12916-017-0913-6.

Licchetta, M. and M. Stelmach (Sept. 2016). *Fiscal sustainability and public spending on health*. Fiscal sustainability analytical paper. Office for Budget Responsibility. URL: http://budgetresponsibility.org.uk/docs/dlm_uploads/Health-FSAP.pdf.

Marengoni, A., S. Angleman, R. Melis, F. Mangialasche, A. Karp, A. Garmen and et al. (2011). 'Aging with multimorbidity: a systematic review of the literature'. *Ageing Research Reviews*, 10: 430–439.

Ng, S., R. Tawiah, M. Sawyer and P. Scuffham (2018). 'Patterns of multimorbid health conditions: a systematic review of analytical methods and comparison analysis'. *International Journal of Epidemiology*, 47: 1687–704. DOI: doi:10.1093/ije/dyy134.

NHS Digital (2009-10). *HRG4 2009/10 Reference Costs Grouper*. URL: https://webarchive.nationalarchives.gov.uk/20171012065725/http://content.digital.nhs.uk/article/2318/HRG4-200910-Reference-Costs-Grouper.

— (2016-17). *Costing HRG4+ 2016/17 Reference Costs Grouper*. URL: https://digital.nhs.uk/services/national-casemix-office/downloads-groupers-and-tools/grouper-and-tools-archive/costing-hrg4-2016-17-reference-costs-grouper.

— (2010). *Hospital Episode Statistics, Admitted Patient Care - England, 2009-10*. URL: https://digital.nhs.uk/data-and-information/publications/statistical/hospital-admitted-patient-care-activity/hospital-episode-statistics-admitted-patient-care-england-2009-10.

— (2017). *Hospital Episode Statistics, Admitted Patient Care - England, 2014-15*. URL: https://digital.nhs.uk/data-and-information/publications/statistical/hospital-admitted-patient-care-activity/2016-17.

NHS England (n.d.[a]). *Bed Availability and Occupancy Data - Day only*. URL: https://www.england.nhs.uk/statistics/statistical-work-areas/bed-availability-and-occupancy/bed-data-day-only/.

— (n.d.[b]). *Bed Availability and Occupancy Data - Overnight*. URL: https://www.england.nhs.uk/statistics/statistical-work-areas/bed-availability-and-occupancy/bed-data-overnight/.

NHS Improvement (n.d.). *Archived Reference Costs*. URL: https://webarchive.nationalarchives.gov.uk/20200501111106/https://improvement.nhs.uk/resources/reference-costs/.

Oaxaca, R. (1973). 'Male-Female Wage Differentials in Urban Labor Markets'. *International Economic Review*, 14: 693–709. ISSN: 00206598, 14682354. URL: http://www.jstor.org/stable/2525981.

Oaxaca, R. L. and M. R. Ransom (1999). 'Identification in Detailed Wage Decompositions'. *The Review of Economics and Statistics*, 81: 154–157. DOI: 10.1162/003465399767923908. eprint: http://dx.doi.org/10.1162/003465399767923908. URL: http://dx.doi.org/10.1162/003465399767923908.

Office for National Statistics (Dec. 2019a). *Past and projected period and cohort life tables, 2018-based, UK: 1981 to 2068*. URL: https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/bulletins/pastandprojecteddatafromtheperiodandcohortlifetables/1981to2068.

— (Jan. 2019b). *Volume growth, contributions to growth and expenditure shares for public service healthcare quantity output by component*. URL: https://www.ons.gov.uk/economy/economicoutputandproductivity/publicservicesproductivity/datasets/publicserviceproductivityestimateshealthcareukandengland.

— (June 2020). *England population mid-year estimate*. URL: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/timeseries/enpop/pop.

Purdy, S., T. Griffin, C. Salisbury and D. Sharp (2009). 'Ambulatory care sensitive conditions: terminology and disease coding need to be more specific to aid policy makers and clinicians'. *Public Health*, 123: 169–73.

Rice, N. and M. J. Aragón (2018). *The determinants of health care expenditure growth*. CHE Research Paper 156. Centre for Health Economics, University of York. URL: https://www.york.ac.uk/media/che/documents/papers/researchpapers/CHERP156_determinants_health_care_expenditure_growth.pdf.

Roland, M. and G. Abel (2012). 'Reducing emergency admissions: are we on the right track?' *British Medical Journal*, 45: DOI: 10.1136/bmj.e6017.

Santos, R., N. Rice and H. Gravelle (2020). 'Patterns of emergency admissions for ambulatory care sensitive conditions: a spatial cross-sectional analysis of observational data'. *BMJ Open*, In Press.

StataCorp. (2019). *Stata Statistical Software: Release 16*. College Station, TX: StataCorp LLC.

Stokes, J., B. Guthrie, S. W. Mercer, N. Rice and M. Sutton (Jan. 2021). 'Multimorbidity combinations, costs of hospital care and potentially preventable emergency admissions in England: A cohort study'. *PLOS Medicine*, 18: 1–16. DOI: 10.1371/journal.pmed.1003514. URL: https://doi.org/10.1371/journal.pmed.1003514.

Whitty, C. J. M., C. MacEwen, A. Goddard, D. Alderson, M. Marshall, C. Calderwood and et al (2020). 'Rising to the challenge of multimorbidity'. *British Medical Journal*, 368: l6964. DOI: doi:10.1136/bmj.l6964.

Yun, M.-S. (2005). 'A Simple Solution to the Identification Problem in Detailed Wage Decompositions'. *Economic Inquiry*, 43: 766–772. ISSN: 1465-7295. DOI: 10.1093/ei/cbi053. URL: http://dx.doi.org/10.1093/ei/cbi053.

A. Appendix A

Table A.1 shows the descriptions of the 22 ICD-10 chapters used to classify diagnoses in the main part. For a description of the diagnoses within each chapter see `https://icd.who.int/browse10/2008/en`.

Table A.1: ICD-10 Classification

	ICD-10 Chapters	Codes
I	Certain infectious and parasitic diseases	A00-B99
II	Neoplasms	C00-D48
III	Diseases of the blood and blood-forming organs and certain immune disorders	D50-D89
IV	Endocrine, nutritional and metabolic diseases	E00-E90
V	Mental and behavioural disorders	F00-F99
VI	Diseases of the nervous system	G00-G99
VII	Diseases of the eye and adnexa	H00-H59
VIII	Diseases of the ear and mastoid process	H60-H95
IX	Diseases of the circulatory system	I00-I99
X	Diseases of the respiratory system	J00-J99
XI	Diseases of the digestive system	K00-K93
XII	Diseases of the skin and subcutaneous tissue	L00-L99
XIII	Diseases of the musculoskeletal system and connective tissue	M00-M99
XIV	Diseases of the genitourinary system	N00-N99
XV	Pregnancy, childbirth and the puerperium	O00-O99
XVI	Certain conditions originating in the perinatal period	P00-P96
XVII	Congenital malformations, deformations and chromosomal abnormalities	Q00-Q99
XVIII	Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	R00-R99
XIX	Injury, poisoning and certain other consequences of external causes	S00-T98
XX	External causes of morbidity and mortality	V01-Y98
XXI	Factors influencing health status and contact with health services	Z00-Z99
XXII	Codes for special purposes	U00-U89