Health policy 132 (2023) 104800

Contents lists available at ScienceDirect

Health policy

journal homepage: www.elsevier.com/locate/healthpol

The impact of different types of NHS expenditure on health: Marginal cost per QALY estimates for England for 2016/17

Stephen Martin [a], Karl Claxton [b], James Lomas [a,*], Francesco Longo [b]

[a] Department of Economics, University of York, York YO10 5DD UK
[b] Centre for Health Economics, University of York, York YO10 5DD, UK

ARTICLE INFO

Keywords:
Healthcare productivity
Healthcare expenditure
Mortality
Two-stage least squares estimation
Cost per quality-adjusted life year

ABSTRACT

English data from 2003 to 2012 suggests that it costs the NHS £10,000 to generate an additional quality-adjusted life year (QALY). This estimate relates to all NHS expenditure and no attempt was made to explore possible heterogeneity within this total. Different types of expenditure – such as secondary care, primary care and specialized commissioning – may have different productivities and estimates of these may help policymakers decide where additional investment is most beneficial. We use the two-stage least squares estimator and data for 2016 to explore the mortality response to three types of healthcare expenditure. Three specifications are estimated for each type of expenditure: backward selection and regularized regression are used to identify parsimonious specifications, and a full specification with all covariates is also estimated. The regression results are combined with information about survival and morbidity disease burden to calculate the marginal cost per QALY for each type of expenditure: the most conservative results suggest that this is about £8,000 for locally (CCG) commissioned services, while estimates for specialized commissioning and primary care are more uncertain. When this heterogeneity is taken into account, the estimated marginal cost per QALY for all NHS expenditure increases slightly, from about £6,000 to £7,000. Our results suggest that additional investment is likely to be most productive in primary care and in locally commissioned services.

1. Introduction

The most recent estimates of the marginal cost per Quality-Adjusted Life Year (QALY) gained (hereafter MCPQ) for all English NHS expenditure are almost a decade old [1,2]. These estimates – ranging from about £6000 to £10,000 – were produced for the period 2003/4 to 2012/13 when the NHS was organised into units of administration known as primary care trusts (PCTs).

Since April 2013 Clinical Commissioning Groups (CCGs) have been responsible for the local administration of NHS healthcare services in England. Each CCG is assigned a fixed annual budget using various centrally determined resource allocation formulae, and CCGs are expected to meet expenditure on most types of healthcare including inpatient and outpatient care, community care and pharmaceuticals from within this budget. Expenditures on specialized services are excluded from this budget on the basis that they are not suitable for local commissioning. This is because specialized services, including chemotherapy, radiotherapy and kidney dialysis, support people with rare and complex conditions and their delivery requires specialist health care professionals, which means that they are not provided in every hospital. Responsibility for both primary medical care (excluding community pharmacy, dentistry and optical services) and specialized commissioning lay with central administrators initially [3,4].

A recent paper presented estimates of the relationship between mortality and locally (CCG) commissioned healthcare services using English data for 2014/15 [5]. Together with information about survival and disease burden, the study estimated how much expenditure – about £7000 – would be required to generate an extra quality-adjusted life year (QALY).

Although local healthcare commissioning accounted for over £65bn of NHS expenditure in 2014/15, specialized commissioning (£14bn) and primary care (£7bn) still accounted for substantial amounts of expenditure but, partly because they were commissioned centrally, these services were excluded from the analysis. These omissions from the expenditure base made it impossible to compare the results – the first since the introduction of Clinical Commissioning Groups (CCGs) in April 2013 – with those reported previously that related to *all* NHS expenditure [1].

* Corresponding author.
E-mail address: james.lomas@york.ac.uk (J. Lomas).

https://doi.org/10.1016/j.healthpol.2023.104800
Received 16 March 2022; Received in revised form 17 March 2023; Accepted 20 March 2023
Available online 21 March 2023

More recently, however, two developments have facilitated the inclusion of these types of spending within the expenditure base. A resource allocation formula with weighted populations and target allocations for specialized services was developed for the first time for CCG areas for 2016/17, and expenditure data for these services for this year is available [6]. In addition, a resource allocation formula with weighted populations and target allocations for primary care at CCG level is also available for 2016/17 and, although expenditure data are not available, allocation data can be used as a proxy for expenditure [7,8].

In this paper we make two contributions to the literature. First, with separate values and separate resource allocation formulae for each type of healthcare expenditure, we estimate the joint impact of each type of expenditure on all-cause mortality and on seven disease-specific measures of mortality. We also examine how sensitive the regression results are to the precise health outcome specification estimated. While theory guides us on the types of variables to be used in our specification, theory is unable to prescribe either specific variables or the functional form that they should follow. These choices instead need to be informed by empirics. We do this by following three approaches to model selection. We use the estimated disease-specific outcome elasticities, together with an existing method for estimating morbidity effects, to calculate the MCPQ for each type of expenditure [9–11]. These results enable us to examine whether previously unexplored heterogeneity across different types of healthcare expenditure affects the MCPQ estimate for total expenditure. We also explore whether this heterogeneity provides any useful policy insights into the allocation of resources between these three different types of healthcare expenditure.

Our second contribution is to present the first estimate of the relationship between health effects and *all* NHS expenditure since the replacement of Primary Care Trusts (PCTs) with CCGs in April 2013. We provide two estimates of this effect and these are compared with those reported previously for PCTs by Lomas et al. [2] and Martin et al. [1]. Our estimates are also compared with estimates that inform the consumption value of health in government appraisals and the threshold used by the UK's regulatory agency NICE to assess whether a new pharmaceutical product should be mandated for use within the NHS.

2. Materials and methods

Sources for the data can be found in Appendix 1.

2.1. Estimating equation

Following other studies that estimate the relationship between health and healthcare expenditure, we assume that health is produced according to a Cobb-Douglas style production function (equation A1 in Appendix 0). Specifically, the mortality rate in a given area is determined by healthcare expenditure per resident, healthcare need and other unspecified local area-specific factors. The regression coefficient on healthcare expenditure reveals how responsive mortality is to a small change in expenditure.

Unlike previous work that has considered either total healthcare expenditure or one type of healthcare expenditure, here the effects of three different types of healthcare expenditure are analysed, and a separate regression coefficient is estimated for each type of expenditure. This permits a comparison of the relative impact of different types of expenditure.

We estimate two specifications: first, we regress mortality on three types of healthcare expenditure (CCG, specialized commissioning and primary care); and second, we regress mortality on the totality of healthcare expenditure. We log-transform all variables and use linear regression methods so that all regression coefficients are elasticities (i.e., they show the percentage change in the mortality rate caused by a 1% change in expenditure). We use the years of life lost rate for all deaths under age 75 as our mortality rate and each type of healthcare expenditure is measured on a per resident basis. The controls for healthcare need are measured on either a per resident or per household basis using population census data for 2011.

2.2. Instrumental variables

Ordinary least squares (OLS) estimates of the elasticity of any healthcare expenditure variable will be biased (positively, i.e. towards finding a null or positive effect of expenditure on mortality) because each type of expenditure is endogenous. Endogeneity arises because each type of healthcare expenditure is a function of a specific allocation formula, and all allocation formulae include information on historic mortality. Both current mortality and historic mortality are a function of unobserved factors (e.g., unobserved health needs). These same unobserved factors will also influence each type of healthcare expenditure so will become unobserved confounders that bias our estimate of the effect of healthcare expenditure on mortality.

We use the two-stage least squares (2SLS) estimator to address the endogeneity issue. This uses one or more exogenous variables ('instruments') that are associated with the exogenous part of the variation in the regressor (expenditure) but which are otherwise unrelated to the dependant variable (mortality). Estimation proceeds in two steps. At the first-stage, each endogenous expenditure variable is regressed on all instruments and controls for healthcare need, and the regression coefficients are used to obtain a predicted value for the 'good' or exogenous variation in expenditure. Then, at the second-stage, this predicted level of expenditure replaces actual expenditure when regressing mortality on expenditure and controls.

Finding appropriate instruments can be difficult. Where funding formulae are used to allocate budgets, Andrews et al. [7] have suggested that exogenous elements of the funding rule be used as instruments. All three types of expenditure studied here are allocated to local areas using different funding formulae but the basic structure of each formula is the same: the funding rule allocates a national average amount per person with adjustments for local differences in the need for healthcare and the cost of meeting these needs.

We use the following as our instruments:

(a) the age-cost index, the local input price index and the 'distance from target' (DFT) index from the funding formula for CCG expenditure;
(b) the local input price index and the DFT index from the formula for specialized commissioning expenditure; and
(c) the DFT index from the formula for primary care.

The age-cost index reflects the impact of the local population's demographic profile on prescribing costs (one component of the CCG allocation). The local input price index reflects the impact of local wage rates and other input prices on CCG and specialized commissioning costs. The DFT index is used as an instrument for each type of expenditure. It reflects how far the actual budget is from its target allocation. Every few years the relevant government department revises the funding formula and this, together with data updates, generates a new target for each authority. The new funding rule might generate a large change in some authorities' target allocations and, to avoid sudden large reductions in actual allocations, such changes are phased into actual budgets over several years in line with the 'pace of change' policy [3].

In principle each instrument is likely to be a strong predictor of the relevant type of expenditure because it is a direct input into the resource allocation formula that underpins how much is allocated to and spent in each local area. However, as weak instruments can be problematic, we report the Sanderson-Windmeijer F test statistic for each endogenous variable in all first-stage regressions (the F statistic should be about 10 or better [12–14]).

In addition to being strong predictors, instruments must meet two other assumptions if 2SLS is to generate consistent estimates. These are the exogeneity and excludability assumptions and detailed arguments in

support of these assumptions for each of our instruments can be found in Appendix 0. Importantly, in the case of this econometric approach (and indeed in most applied work), the instruments are argued only to be conditionally exogenous and excludable. In other words, these assumptions are met once controls for healthcare need are included. For example, high local input prices may reflect relative economic prosperity that may be associated with lower healthcare need and therefore lower mortality. In the absence of controls for healthcare need, use of this instrument will not be able to isolate the causal effect of expenditure on mortality. The exclusion assumption is tested empirically using the Hansen-Sargan test and the specification is adjusted (in the very few cases) where this test suggests that adjustment is necessary [15].

2.3. Selection of controls

2.3.1. Full specification

Following other English studies and to aid comparability, we obtain thirteen socio-economic variables as potential controls for healthcare need that are candidates based upon the underlying theory [9]. For each disease area, we start by estimating the 'full' specification with all socio-economic variables included as controls. These socio-economic variables are described in appendix 1.

2.3.2. Backward selection specification

With only 212 CCGs for analysis, we also pursue a more parsimonious specification using two different methods of model selection. First, we estimate a 'backward selection specification', which involves removing the least significant regressor from the full specification and re-estimating the equation, and this process continues until there are only significant controls remaining (the expenditure term is always included).

2.3.3. IV lasso specification

As the backward selection of covariates is not universally popular [16], we use regularised linear regression to find a second smaller set of controls. Regularised regression minimises the sum of squared deviations between the observed and model predicted values, but it also imposes a regularization penalty aimed at limiting model complexity. The most popular regularised regression method is the 'lasso'. This penalises the sum of the absolute size of the coefficient estimates and hence it acts as a model selection technique because the lasso sets some of the coefficient estimates to zero [17–19].

Regularized regression alone does not produce estimates that can be interpreted as causal. Hence we adopt one of the estimators that have been derived to provide reliable inference for the variable of interest (healthcare expenditure) after using lasso-based covariate selection to determine which variables belong in the set of controls. We estimate the post-double-selection (PDS) regularized regression specification introduced by Belloni, Chernozhukov and Hansen [20] using the user-written *ivlasso* command in *Stata 16* [18,21].

2.3.4. Estimation

We begin by estimating the health outcome equation with total NHS expenditure as the expenditure variable. We estimate three specifications – full, backwards selection and lasso – for all-cause mortality and for each disease-specific measure of mortality. We then re-estimate with three separate types of healthcare expenditure in each health outcome specification.

All observations are weighted by the size of the local population and robust standard errors are reported. Estimation uses the *Stata* statistical package and the *ivreg2* command [12]. In addition to the tests of instrument validity and strength, we also report the Pesaran-Taylor test for mis-specification for every second-stage regression and the specification is adjusted (in the very few cases) where this test suggests that adjustment is necessary [22].

2.4. Data

All-cause and disease-specific mortality data for England were obtained from NHS Digital. We use the age/sex standardised years of life lost rate (SYLLR) as our mortality measure and this is calculated for all deaths under the age of 75 years pooled over the three calendar years for 2016/2017/2018 [23]. These data are not available for CCGs but are available for 152 local authorities. Hence all CCG-based variables were converted to a local authority (LA) geography using the proportion of the population in each CCG that mapped into each local authority as at mid-2012. There is a one-to-one correspondence between CCG and LA geographical boundaries for over half of all LAs.

NHS England kindly supplied CCG expenditure data for the financial year 2016/17. Specialized commissioning expenditure data for 2016/17 were also obtained from NHS England. Primary care *expenditure* data at CCG level is not available so we use *allocation* data instead. By studying the impact of expenditure for the financial year 2016/17 on mortality for the three calendar years 2016/2017/2018, we are implicitly assuming that the effect of current expenditure on future mortality is the same as the impact of previous expenditure on current mortality so that these two effects cancel out each other.

As table A1 in Appendix 1 shows, average CCG healthcare expenditure per person in 2016/17 was £1263 and this varied between £1015 and £1663. Specialized commissioning expenditure was £250 per resident and the primary care allocation was £128 per resident. The all-cause SYLLR averaged 442 years of life lost per 10,000 head of population. For reasons of space, details of and descriptive statistics for the control variables and instruments are in appendix 1.

2.5. Calculating the MCPQ

For each disease area estimation will produce a set of elasticities that show how responsive mortality is to small changes in healthcare expenditure. Yet mortality is only one dimension of the health outcome and almost half of NHS expenditure is in disease areas where mortality is very limited. In addition, morbidity is a considerable aspect of the disease burden where a mortality indicator is available.

We do not have quality of life data by disease and local area and hence we cannot directly estimate the impact of expenditure on a comprehensive measure of health that incorporates both survival and quality effects. Instead, we are forced to make some assumptions about how the observed impacts on mortality might translate into what are unobserved effects on survival and the quality of life.

To estimate the full QALY effect of healthcare expenditure, previous work has made two assumptions: first, that the impact of a change in expenditure on the *mortality* burden of disease can be used as surrogate for the likely impact on the *QALY* burden of disease; and second, that the impact on the burden of disease in those disease areas *with* a mortality indicator can be extrapolated to estimates of the QALY burden of disease in those disease areas *without* a mortality indicator. Translating the estimated mortality elasticities into overall absolute QALY effects requires taking account of the heterogeneity by disease area both in terms of disease-specific elasticities and the QALY burden of disease. We use this method to calculate the MCPQ for each type of healthcare expenditure studied here. Further details about this method, the plausibility of the assumptions involved, and how the QALY burden of disease is calculated can be found elsewhere [1,10,11,24].

3. Results

3.1. Regression results for all-cause mortality

In Tables 1 and 2 we present the regression results for all-cause mortality in some detail to illustrate our approach. Thereafter we only present the estimated elasticities of the healthcare expenditure variables and the associated MCPQ estimates.

Table 1
All-cause health outcome results for total healthcare expenditure, 2016/17.

	(1)	(2)	(3)	(4)	(5)	(6)
	All-cause mortality	All-cause mortality	All-cause mortality	All-cause mortality	All-cause mortality	All-cause mortality
	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18
	no control variables	final full specification	final full specification	no control variables	backwards selection specification	PDS-selected variables
VARIABLES	no instruments	no instruments	three instruments	three instruments	three instruments	three instruments
Healthcare expenditure variable						
Total healthcare expenditure per resident	1.312***	−0.266**	−1.595***	1.797***	−1.553***	−1.771***
	[0.155]	[0.134]	[0.336]	[0.281]	[0.209]	[0.385]
Observations	151	151	151	151	151	151
Ramsey reset p-value	0.657	0.375				
Endogeneity p-value			0.000	0.143	0.000	
Reduced form R^2			0.932	0.658	0.920	0.922
Hansen-Sargan p-value			0.454	0.000	0.687	
Kleibergen-Paap F statistic			14.785	35.528	30.991	
First stage R^2			0.876	0.369	0.836	0.869
Pesaran-Taylor p-value			0.975	0.704	0.268	

Notes: {1] Robust standard errors in brackets. [2] *** $p<0.01$, ** $p<0.05$, * $p<0.1$. [3] The three selected instruments are the age-cost index, the local input price index and the DFT index from the funding formula for CCG expenditure.

Table 2
All-cause health outcome results for CCG core, specialized commissioning and primary care expenditure, 2016/17.

	(1)	(2)	(3)	(4)	(5)	(6)
	All-cause mortality	All-cause mortality	All-cause mortality	All-cause mortality	All-cause mortality	All-cause mortality
	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18	SYLLR 2016/17/18
	no control variables	final full specification	final full specification	no control variables	backwards selection specification	PDS-selected variables
VARIABLES	no instruments	no instruments	six instruments	six instruments	six instruments	six instruments
Healthcare expenditure variables						
CCG expenditure per resident, 2016/17	0.718***	−0.144	−1.103***	1.230***	−1.200***	−1.053***
	[0.151]	[0.114]	[0.248]	[0.205]	[0.199]	[0.265]
SpecComm expenditure per resident, 2016/17	0.174*	−0.057	−0.051	0.546***	−0.130	−0.088
	[0.096]	[0.048]	[0.113]	[0.136]	[0.089]	[0.110]
Primary Care expenditure per resident, 2016/17	0.752***	−0.234***	−0.442***	0.818***	−0.445***	−0.424***
	[0.198]	[0.087]	[0.132]	[0.220]	[0.133]	[0.129]
Observations	151	151	151	151	151	151
Ramsey reset p-value	0.730	0.385				
Endogeneity p-value			0.000	0.024	0.000	
Reduced form R^2			0.937	0.685	0.923	0.936
Hansen-Sargan p-value			0.258	0.000	0.665	
Pesaran-Taylor p-value			0.891	0.881	0.192	
SW_CCG F-statistic			15.644	37.236	23.572	
CCG first stage R^2			0.892	0.506	0.883	0.891
SW_SpecComm F-statistic			16.361	26.840	16.549	
SpecComm first stage R^2			0.771	0.539	0.685	0.770
SW_PCare F-statistic			91.862	77.920	55.424	
PCare first stage R^2			0.957	0.718	0.913	0.956

Notes: {1] Robust standard errors in brackets. [2] *** $p<0.01$, ** $p<0.05$, * $p<0.1$. [3] CCG=Clinical Commissioning Group; SW=Sanderson-Windmeijer. [4] In the absence of control variables, the reduced form R^2 is and the CCG, specialised commissioning and primary care first-stage R^2s are X, Y and Z respectively.

Estimation of the outcome equation using total NHS healthcare expenditure with no controls and instruments generates the result shown in column 1 of Table 1. The resulting elasticity of expenditure is positive and strongly significant. This reflects that allocations are based on healthcare need. The inclusion of control variables that are proxies of healthcare need is sufficient to reverse the sign of the estimated elasticity of expenditure as shown in column 2. Column 3 provides the results from the instrumental variable regression based on the full set of controls, and column 4 gives the results from the instrumental variable regression in the absence of any control variables. Starting with the specification with the full set of controls, application of backward selection produces the result shown in column 5 and the application of the lasso to the controls for healthcare need generates the result in column 6. All three specifications (in columns 3, 5 and 6) produce similar results with an elasticity of total healthcare expenditure ranging from −1.553 (the backwards selection specification) to −1.771 (the lasso). The difference between the results in these three columns and the result in column 2 shows that controlling for healthcare need is not sufficient because it does not account for all sources of endogeneity including that resulting from allocations being based, in part, on historical mortality. The average number of annual deaths in 2016–2018 was 499,000 and total healthcare expenditure in 2016/17 was £93,800,000,000. These elasticities imply that a 1% increase in total healthcare expenditure (£938,000,000) would be expected to reduce deaths by between 1.553%

(7750) and 1.771% (8840), which equates to a cost per death averted of between £106,000 to £121,000.

Estimation of outcome elasticities using three separate types of healthcare expenditure is presented in a similar format in Table 2. Elasticities of all three types of healthcare expenditure are positive and statistically significant when no controls are used (column 1), but the signs of these elasticities are reversed when controls are introduced (column 2). The full specification instrumental variable regression (column 3) returns negative and statistically significant effects of CCG and primary care expenditure, but not specialized commissioning. The application of backward selection to this specification generates the result shown in column 5 and the lasso generates the result in column 6. All three specifications generate similar significant negative elasticities of CCG expenditure (about −1.1) and primary care expenditure (about −0.4). CCG expenditure was £72,200,000,000 in 2016/17 and primary care expenditure £7340,000,000. The elasticities imply a cost per death averted of £141,000 for CCG expenditure and £36,800 for primary care expenditure. There is a small negative but statistically insignificant elasticity of specialized commissioning expenditure.

3.2. Outcome elasticities with the sum of healthcare expenditure

The estimated effects of total healthcare expenditure on mortality by disease area and by regression specification are summarised in Table 3; see rows 1 to 8 of columns 1 (full specification), 2 (backwards selection specification) and 3 (lasso specification). As expected, all elasticities are negative, and only five of the 24 are not statistically significant at the 10% level. The five insignificant elasticities occur with mortality from either diabetes or epilepsy and these are the disease areas with the smallest number of deaths.

The disease-specific elasticities in rows 2 to 8 can be used to calculate an implied all-cause elasticity (see row 9). This involves summing the product of the number of deaths and the elasticity across all disease areas, and dividing this sum by the total number of deaths across the same disease areas. Although there are three different values, they are very similar and range between −1.456 and −1.746. Across all three specifications, the average implied and actual all-cause elasticities are almost identical.

Finally, the disease-specific elasticities in rows 2 to 8, together with burden of disease information and the extrapolation and surrogacy assumptions outlined above, can be used to calculate the MCPQ associated with total NHS expenditure for each of the three different specifications. These estimates are in row 10. They are very similar and range between £5375 (full specification) and £5767 (backwards selection specification). The 95% confidence intervals for each estimate overlap considerably, with the upper bound falling below £15,000 in all cases.

More detailed regression results for seven disease-specific measures of mortality are in the appendices. In particular, appendices 2 and 3 contain (first- and second-stage) estimates with total healthcare expenditure as the sole expenditure variable; and appendices 4 and 5 contain estimates with separate totals for CCG, specialized commissioning and primary care expenditure.

3.3. Outcome elasticities with three types of healthcare expenditure

The results summarised in Table 4 indicate the effect on disease-specific measures of mortality of each of the three types of healthcare expenditure. We report the elasticities grouped by type of expenditure rather than by specification. This facilitates a comparison of the impact that different specifications – full, backwards selection, lasso – have on the results for a given type of expenditure. Results with only CCG expenditure in the health outcome equation are in appendix 6.

3.3.1. Elasticities - CCG expenditure

With the exception of epilepsy mortality, the elasticities of CCG expenditure for a given disease area are reasonably similar for all three specifications. The only insignificant elasticity of CCG expenditure is in the backwards selection specification for epilepsy mortality; all of the others are significant at the 10% level or better.

3.3.2. Elasticities - Specialized commissioning

All three specifications for all-cause, cancer and respiratory mortality generate a statistically insignificant negative elasticity of the specialized commissioning expenditure variable. The elasticity of specialized commissioning expenditure in the other disease areas are more mixed with a variety of positive and negative elasticities but, again, none is significant.

3.3.3. Elasticities - Primary care expenditure

For all-cause mortality, and for each of the four disease-specific areas with the largest number of deaths, the elasticity of primary care expenditure is negative and very similar across all three specifications. Also, all of these 15 elasticities are statistically significant. For two of the other three disease areas, there is a negative elasticity of primary care expenditure for all three specifications but these elasticities are not significant.

3.3.4. Implied all-cause elasticities and MCPQ estimates

Across the three specifications estimated, the actual (row 1) and implied (row 9) all-cause elasticities are almost identical. MCPQ estimates for each type of expenditure and for each specification are in row 10 of Table 4. The calculation of these estimates is complicated by the fact that some of the estimated elasticities of expenditure have positive values. With one exception, these positive values are not statistically significant but they do imply – somewhat counterintuitively – that healthcare expenditure has a positive impact on the mortality rate. The MCPQ for *CCG expenditure* is just over £5000 using the full and lasso specifications, and just over £8000 using the backwards selection specifications. The MCPQ associated with specialized commissioning ranges from £26,000 (full specification), to £41,000 (backwards selection specification), and then to -£10,509 (lasso specification). The negative estimate implies that additional expenditure will increase mortality and that less expenditure would reduce it. Finally, the MCPQ associated with primary care expenditure ranges between £3000 (backwards selection specification) and £12,000 (lasso specification).

The impact of replacing positive elasticities with a zero value is shown in appendix 7. As there are no positive estimated elasticities of CCG core expenditure, the MCPQ associated with this type of expenditure is unchanged. The MCPQ associated with *specialized commissioning* ranges between £11,000 (full specification) and £33,000 (lasso). Finally, the MCPQ associated with *primary care expenditure* is about £2000 for all three specifications.

3.3.5. MCPQ estimates for all expenditure using disaggregated expenditure results

The implied all-cause mortality elasticities associated with each type of healthcare expenditure in row 9 of Table 4 can be added together to obtain an implied all-cause elasticity for the sum of CCG, specialized commissioning and primary care expenditure for each specification type (full/backwards selection/lasso). These 'total expenditure' implied all-cause elasticities are shown in columns 10 (full), 11 (backwards selection) and 12 (lasso) of Table 4. These 'implied all healthcare expenditure' elasticities can be used to calculate the associated MCPQ and these estimates are in row 10 of columns 10 to 12 in Table 4.

There is little variation in these estimates with all three falling between £6000 and just over £8000. Once again, the type of specification – full, backwards selection or lasso – has little effect on the MCPQ estimates. If positive regression elasticities are replaced with zero values then similar results are obtained and all three estimates lie between £5000 and £7000 (see appendix 7).

3.4. Comparing alternative MCPQ estimates

Using separate totals for each type of healthcare expenditure, the estimated MCPQ ranges from £6098 to £8039 (Table 4). If we use the sum of healthcare expenditure, the estimated MCPQ ranges from £5375 to £5767 (Table 3).

4. Discussion

The most recent estimates of the MCPQ for all English NHS expenditure are almost a decade old [1,2]. These estimates – ranging from about £6000 to £10,000 – for the period 2003/4 to 2012/13 have not been updateable until now, partly because there was no information about the size of local expenditure on centrally commissioned services such as on specialized commissioning. However, a resource allocation formula for specialized commissioning was introduced in 2016/17 and this coincided with the availability of expenditure data at the local level.

We have presented two sets of MCPQ estimates for total NHS expenditure in 2016/17. If CCG, primary care and specialized commissioning expenditure are included separately then, using the full specification, we obtain a MCPQ for all NHS expenditure of £6098 (and a confidence interval of £4237 to £10,919). Alternatively, if these three types of expenditure are added together when estimating the health outcome equation then we obtain a MCPQ of £5375 (and a confidence interval of £3580 to £10,765). These point estimates are lower than previous estimates but the confidence intervals for the 2016/17 estimates overlap those associated with the estimates for 2003/4 to 2012/13 (which ranged from £4000 to £23,000 [1]). The confidence intervals presented in this paper, and in other papers in this literature, do not reflect all forms of uncertainty. They only reflect sampling uncertainty in the estimated disease-specific elasticities and do not reflect, for example, any uncertainties associated with the extrapolation and surrogacy assumptions to link mortality effects to health effects more generally, and any inevitable uncertainties that remain over the validity of the instrumental variable approach after considering the qualitative and quantitative assessments provided.

In our identification strategy, we argue that the IVs are only exogenous (not directly related to mortality) when additional control variables are included. While IVs would ideally be unconditionally exogenous, this is rarely the case in applied work. Even in instances where an IV is based on random assignment, additional controls may still be required [25]. The conditional exogeneity of the IVs in this analysis means that the selection of control variables is especially critical. With little theory to guide functional form or the choice of specific controls, selection based on empirical performance can be used [26,27]. However, it is worth noting that selection processes based on an in-sample approach, such as those implemented in this paper, can be counter-productive in some circumstances [28]. The results from this paper are, however, found to be consistent regardless of the selection process followed, including when no selection process is implemented, (see Appendix 2 for details of all estimated models). Nonetheless, there may inevitably remain concerns for residual confounding that are a source of uncertainty not captured within the estimated confidence intervals.

The results in this paper contribute to a growing body of evidence where a consistent finding that the MCPQ is not greater than £15,000. £15,000 per QALY is used as a benchmark in impact assessments used by the Department of Health and Social Care [29] and is not found to be too low in this work. This means that, on average, spending an additional £15,000 on NHS services would be expected to produce at least one QALY. It also means that cuts of the same magnitude would reduce health production by at least one QALY. £15,000 per QALY lies below the threshold (£30,000) used by the UK's regulatory agency (NICE) when considering whether to mandate the use of a new drug within the NHS, which suggests that new drugs are approved that do more harm than good [24]. In addition, £15,000 per QALY is also considerably lower than the consumption value of health employed by the UK Treasury (£70,000) [30], which implies that the NHS provides very good value-for-money and that expansions of its budget may be justified.

We have also exploited the availability of expenditure by different types of healthcare to estimate the effects on mortality and the associated MCPQ for each of them. Our point estimates suggest that the MCPQ for CCG expenditure is between £5000 and £8000 with a confidence interval of between £3500 and £13,000. Looking at all-cause mortality, the effects of primary care expenditure appear large in comparison to CCG expenditure, but the MCPQ results for primary care are more uncertain and variable across specifications. We have been unable to find a statistically significant effect for specialized commissioning on mortality. This is plausible as such expenditure often buys costly and relatively rare services and the impact on mortality maybe difficult to detect.

Notwithstanding this issue, the MCPQ estimates for each type of NHS expenditure could be used to inform where any additional investment might be most productive of health. For example, it is difficult to ignore the result that the MCPQ for CCG and primary care expenditure are considerably lower than that for specialized commissioning expenditure, and hence the conclusion must be that any additional investment should initially focus on these areas in order to produce the greatest health benefit.

One potential weakness with previous English studies is that they only used backward selection to identify a plausible specification for the health outcome equation [1]. Our results suggest that the full, backward selection and regularised regression approaches generate very similar results for CCG and total NHS expenditure but that this is not the case for primary care and to an even greater extent specialized commissioning where the mortality signal may be relatively weak. However, when all three types of expenditure are considered together then, once again, the full, backward selection and regularised regression results generate very similar MCPQ estimates.

Finally, our results also demonstrate that they are largely robust to unanticipated estimated elasticities of the expenditure variables. In particular, the overall MCPQ estimates are largely unaffected whether positive estimated elasticities of the expenditure variable are replaced with zero values or not.

Table 3
Regression coefficients on total healthcare expenditure and marginal cost per QALY estimates, 2016/17.

Regression coefficients on healthcare expenditure and cost per QALY estimatesAll specifications use the sum of three types of healthcare expenditure			
	2016/17 Total expenditure full specification	2016/17 Total expenditure backwards selection specification	2016/17 Total expenditure IV lasso
Mortality by disease area	column 1	column 2	column 3
1 All-cause mortality	−1.595***	−1.553***	−1.771***
2 Cancer	−0.878***	−0.987***	−1.187***
3 Circulatory disease	−1.948***	−1.665***	−1.975***
4 Gastro-intestinal (liver)	−5.566***	−5.398***	−5.628***
5 Respiratory disease	−3.649***	−2.549***	−3.866***
6 Infectious disease	−2.650**	−1.271***	−2.183*
7 Diabetes	−1.808	−0.987	−1.555
8 Epilepsy	−1.438	−1.968*	−1.160
9 Implied all-cause mortality	−1.650	−1.456	−1.746
10 Marginal cost per QALY (£)	£5375	£5767	£5460
95% confidence interval	£3580, £10,765	£3994, £10,458	£3719, £10,321

Table 4
Regression coefficients on specific types of healthcare expenditure and marginal cost per QALY estimates, 2016/17.

Regression coefficients on healthcare expenditure and marginal cost per QALY estimatesAll specifications include three types of healthcare expenditure										Marginal cost per QALY estimatesAll specifications include three types of healthcare expenditure		
	2016/17 CCG expenditure	2016/17 CCG expenditure	2016/17 CCG expenditure	2016/17 Specialized commissioning	2016/17 Specialized commissioning	2016/17 Specialized commissioning	2016/17 Primary care allocation	2016/17 Primary care allocation	2016/17 Primary care allocation	2016/17 All components combined	2016/17 All components combined	2016/17 All components combined
	full	backwards selection	IV lasso	full	backwards selection	IV lasso	full	backwards selection	IV lasso	full	backwards selection	IV lasso
Mortality by disease area	column 1	column 2	column 3	column 4	column 5	column 6	column 7	column 8	column 9	column 10	column 11	column 12
1 All-cause mortality	−1.103***	−1.200***	−1.053***	−0.051	−0.130	−0.088	−0.442***	−0.445***	−0.424***			
2 Cancer	−0.551***	−0.386***	−0.658***	−0.112	−0.044	−0.101	−0.309***	−0.248***	−0.311***			
3 Circulatory disease	−1.199***	−1.260***	−1.252***	0.174	0.196	0.161	−0.561***	−0.542***	−0.549***			
4 Gastro-intestinal (liver)	−3.754***	−3.174***	−3.131***	0.262	0.264	0.156	−1.167***	−1.259***	−1.201***			
5 Respiratory disease	−2.594***	−2.737***	−2.756***	−0.216	−0.225	−0.190	−1.060***	−1.199***	−1.143***			
6 Infectious disease	−2.115**	−1.163**	−2.029**	−0.090	−0.095	0.105	−0.304	−0.319	−0.121			
7 Diabetes	−1.632*	−1.398**	−1.598*	0.499	0.153	0.587	−0.601	−0.614	−0.346			
8 Epilepsy	−1.456*	−0.062	−1.563*	−0.256	−0.147	0.379	0.861	0.527	1.041*			
9 Implied all-cause mortality	−1.129	−0.990	−1.169	−0.014	0.012	0.028	−0.389	−0.410	−0.381	−1.534	−1.388	−1.525
10 Marginal cost per QALY	£5335	£8071	£5159	£26,541	£40,819	-£10,295	£5841	£3077	£11,954	£6098	£8039	£7109
95% confidence interval	£3878, £8546	£5842, £13,057	£3649, £8788	£4510, -£6773	£6081, -£8381	£8139, -£3121	£1422, -£2841	£1299, -£9180	£1727, -£2366	£4237, £10,919	£5543, £14,249	£4545, £16,561

NB [1]*** denotes p-value<0.01, ** denotes p-value<0.05, * denotes p-value<0.10.
[2] The results are grouped by type of expenditure rather than by specification. The full specification result for any disease area would consist of the coefficient in column 1 for CCG expenditure, the coefficient in column 4 for specialised commissioning, and the coefficient in column 7 for primary care.

5. Conclusion

This paper has presented estimates of the MCPQ for three types of NHS healthcare expenditure in 2016/17. Our results include the first estimates for two types of expenditure – for specialized commissioning and for primary care – and they suggest that, of the three types of expenditure studied, additional investment is likely to be most productive if directed towards primary care and CCG expenditure. In addition to the disaggregated results, we have also presented the first MCPQ estimates for *all* NHS expenditure since 2012/13. These suggest that, if anything, the marginal cost has fallen to, at most, £8000 with a 95% confidence interval of between £5500 and £14,200.

Declarations of Competing Interest

None.

Funding

This research was funded by the National Institute for Health Research (NIHR) Policy Research Programme, conducted through the Policy Research Unit in Economic Methods of Evaluation in Health and Social Care Interventions, PR-PRU-1217–20401. The views expressed are those of the authors and not necessarily those of the NIHR or the Department of Health and Social Care. Although the results have been presented to the Department and members have commented on the research, the Department of Health and Social Care had no involvement in: the study design; the collection, analysis and interpretation of the data; the writing of the paper; and the decision to submit the article for publication.

Acknowledgements

This research is funded by the National Institute for Health Research (NIHR) Policy Research Programme, conducted through the Policy Research Unit in Economic Methods of Evaluation in Health and Social Care Interventions, PR-PRU-1217–20401. We would like to thank NHS England for supplying the expenditure data and the Clinical Indicators team at NHS Digital for supplying the mortality data. Stephen (Steve) Martin died on the 4th June 2022. Steve was an outstanding applied econometrician with a passion for working with large datasets and using them to address complex but important policy questions. His work was always meticulous, and he displayed immense clarity in conducting and communicating complex analyses. An exceptional team player, Steve will be profoundly missed by his many friends and colleagues.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.healthpol.2023.104800.

References

[1] Martin, S., Lomas, J., Claxton, K. and Longo, F. (2021). How Effective is Marginal Healthcare Expenditure? New Evidence from England for 2003/04 to 2012/13. Applied Health Economics and Health Policy. 10.1007/s40258-021-00663-3 (accessed 05 October 2021).

[2] Lomas J, Martin S, Claxton K. Estimating the marginal productivity of the english national health service from 2003 to 2012. Value Health 2019;22(9):995–1002.

[3] DH/NHS England. Technical guide to the formulae for 2014-15 and 2015-16 revenue allocations to clinical commissioning groups and area teams. Department of Health 2014. Available at, https://www.england.nhs.uk/allocations/allocations-2014-15-and-2015-16. accessed 05 October 2021.

[4] Peckham S., Falconer J., Gillam S., et al. The organisation and delivery of health improvement in general practice and primary care: a scoping study. Southampton (UK): NIHR Journals Library; 2015 Jun. (Health Services and Delivery Research, No. 3.29.) Chapter 7, Impact of changes in the Health and Social Care Act 2012 and Public Health White Paper. Available from: https://www.ncbi.nlm.nih.gov/books/NBK299613/(accessed 05 October 2021).

[5] Martin, S., Lomas, J., Claxton, K. Longo, F. (2022). How responsive is mortality to locally administered healthcare expenditure? Estimates for England for 2014/15. Applied Health Economics and Health Policy, forthcoming.

[6] NHS England (2016a). Specialised services formula. Available from: https://www.england.nhs.uk/wp-content/uploads/2016/04/4-specialised-services-formula.pdf (accessed 05 October 2021).</number>.

[7] Andrews M, Elamin O, Hall AR, Kyriakoulis K, Sutton M. Inference in the presence of redundant moment conditions and the impact of government health expenditure on health outcomes in England. Econom Rev 2017;36(1–3):23–41. 2017See, https://www.tandfonline.com/doi/full/10.1080/07474938.2016.1114205. accessed 05 October 2021.

[8] NHS England (2016b). Primary care allocations (medical). Available from: https://www.england.nhs.uk/publication/nhs-england-allocations-primary-care-medical (accessed 05 October 2021).</number>.

[9] Claxton K, Martin S, Soares M, Rice N, Spackman E, Hinde S, Devlin N, Smith PC, Sculpher M. Methods for the estimation of the cost-effectiveness threshold. Health Technol Assess 2015;19(14):1–503. 2015 Febv-viAvailable at, https://www.ncbi.nlm.nih.gov/pubmed/25692211. accessed 05 October 2021.

[10] Soares M, Sculpher M, Claxton K. Health Opportunity costs: assessing the implications of uncertainty using elicitation methods with experts. Med Decis Making 2020;40. https://doi.org/10.1177/2F0272989X20916450. no 4. Seeaccessed 05 October 2021.

[11] Soares M, Sculpher M, Claxton K. Authors' response to: "health opportunity costs and expert elicitation: a comment on Soares et al." by Sampson, Firth, and Towse. Med Decis Making February 2021. https://doi.org/10.1177/0272989X20987222. Seeaccessed 05 October 2021.

[12] Baum, C.F., Schaffer, M.E., Stillman, S. (2016). ivreg2: stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression. Available from: http://ideas.repec.org/c/boc/bocode/s425401.html (accessed 05 October 2021).

[13] Sanderson E, Windmeijer F. A weak instrument F-test in linear IV models with multiple endogenous variables. J Econom 2016;190(2):212–21. https://doi.org/10.1016/j.jeconom.2015.06.004. Available ataccessed.

[14] Staiger D, Stock J. Instrumental variables regression with weak instruments. Econometrica 1997;65:557–86. https://doi.org/10.2307/2171753. Available ataccessed 05 October 2021.

[15] Wooldridge JM. Econometric analysis of cross section and panel data. 2nd edition. MIT Press; 2010.

[16] Harrell F. Regression modelling strategies: with applications to linear models, logistic and ordinal regression, and survival analysis. Springer Series in Statistics; 2015.

[17] Ahrens, A., Hansen, C.B., Schaffer, M.E. (2018). pdslasso and ivlasso: progams for post-selection and post-regularization OLS or IV estimation and inference. Available from http://ideas.repec.org/c/boc/bocode/s458459.html (accessed 05 October 2021).

[18] Ahrens A, Hansen CB, Schaffer M. Lassopack: model selection and prediction with regularized regression in Stata. Stata J 2020;20(1):176–235. https://doi.org/10.1177/1536867X20909697. Available fromaccessed 05 October 2021.

[19] Tibshirani R. Regression Shrinkage and Selection via the Lasso. J R Stat Soc B 1996; 58(1):267–88. Available at, http://www.jstor.org/stable/2346178. accessed 05 October 2021.

[20] Belloni A, Chernozhukov V, Hansen C. Inference on treatment effects after selection among high-dimensional controls. Rev Econ Stud 2014;81:608–50. https://doi.org/10.1093/restud/rdt044. Available fromaccessed 05 October 2021.

[21] Drukker, D., and Liu, Di (2019). Using the lasso for inference in high-dimensional models. The Stata Blog, 9 September. Available at https://blog.stata.com/2019/09 (accessed 05 October 2021).

[22] Pesaran MH, Taylor LW. Diagnostics for IV regressions. Oxf Bull Econ Stat 1999;61 (2):255–65. https://doi.org/10.1111/1468-0084.00128. Available fromaccessed.

[23] Lakhani A., Olearnik H. and Eayres D. eds (2006). Compendium of clinical and health indicators: data definitions and user guide for computer files. London: national Centre for Health Outcomes Development. An updated version (December 2015) is available at: https://files.digital.nhs.uk/60/236EC2/Compendium%20User%20Guide%202015%20Dec%20Annex%203%20V1.pdf (accessed 05 October 2021).

[24] Claxton K, Sculpher M, Palmer S, Culyer AJ. Causes for concern: is NICE failing to uphold its responsibilities to all NHS patients? Health Econ 2015;24(1):1–7. Available at, http://www.ncbi.nlm.nih.gov/pubmed/25488707.

[25] Angrist Joshua, Pischke Jörn-Steffen. Mostly harmless econometrics: an empiricist's companion. Princeton University Press; 2009.

[26] Belloni A, Chernozhukov V, Hansen C. High-Dimensional Methods and Inference on Structural and Treatment Effects. J Econ Perspect 2014;28(2):29–50. Available from, https://www.aeaweb.org/articles?id=10.1257/jep.28.2.29. accessed 16 March 2023.

[27] Windmeijer F, Farbmacher H, Davies N, Davey Smith G. On the use of the lasso for instrumental variables estimation with some invalid instruments. J Am Stat Assoc 2019;114(527):1339–50. https://doi.org/10.1080/01621459.2018.1498346. accessed 16 March 2023.

[28] Hall AR, Rudebusch GD, Wilcox DW. Judging instrument relevance in instrumental variables estimation. Int Econ Rev (Philadelphia) 1996:283–98. Available at, https://www.jstor.org/stable/2527324. accessed 16 March 2023.
[29] DHSC, 2020. Statutory scheme to control costs of branded health service medicines. Available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/859212/statutory-scheme-to-control-costs-of-branded-medicines-impact-assessment.pdf.
[30] HM Treasury. 2022. The Green Book: appraisal and evaluation in central government. Available at https://www.gov.uk/government/publications/the-green-book-appraisal-and-evaluation-in-central-governent/the-green-book-2020.