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Abstract

Quasi-experimental studies of mortality variation and trends among large administrative areas of England in the 2000s and early 2010s have suggested that more deprived populations gain larger mortality benefits from marginal increases in public expenditure on secondary care and, consequently, bear a larger share of the health opportunity costs of cost-increasing technologies and programmes. We took a closer look by examining mortality variation in 2018 among 32,784 small areas with a mean population of 1,700, allowing more fine-grained measurements of deprivation and mortality. To identify causal effects of marginal changes in expenditure, we used cross-sectional data on secondary care funding allocated to 195 National Health Service administrative areas in England in 2018/19 and employed a well-established instrumental variable approach based on the "distance from target" component of the funding formula, which generates quasi-exogenous variation in funding based on historical factors unrelated to the need for secondary care. We found an inverted-U shape pattern of mortality gains by deprivation group, whereby the middle group gained significantly more than others. However, we could not reject the null hypothesis that the two more deprived groups received the same mortality gain as the two less deprived groups. These findings were robust to extensive sensitivity analysis using different levels of analysis, control variables, mortality outcomes, functional forms, first stage regression specifications, and exclusions, and our preferred specifications all satisfied standard instrumental variable diagnostic tests. We conclude that the poor do not always gain more from marginal increases in public expenditure on secondary care and, conversely, do not always bear the largest share of the health opportunity costs of cost-increasing programmes.

Keywords: Equity, health inequality, deprivation, geographical resource allocation, instrumental variables, mortality, secondary care expenditure, socioeconomic factors, small area variation.

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1. Introduction

Policy concern about health inequality is increasingly prominent following the COVID-19 crisis (McGowan & Bambra 2022). However, although numerous studies have examined the overall impact of marginal changes in health spending on mortality (Gallet & Doucouliagos 2017; Chavarria Pino et al 2023), less is known about the health inequality impact ie how the overall impact varies between more and less socially advantaged groups (Cookson et al 2021). This information could potentially be useful to inform cross-government negotiations about total national healthcare budgets (Doherty & Sayegh 2022) and geographical healthcare resource allocation between sub-national administrative areas (Smith 2008). It could also be useful when quantifying the net health inequality impacts of cost-increasing new health technologies and programmes using distributional cost-effectiveness analysis, by informing benchmark estimates of the social distribution of health opportunity costs (Cookson et al 2020).

There is a growing international literature linking variation in health expenditure and mortality across large sub-national administrative areas, including cross-sectional instrumental variable studies in Australia, Sweden and England and panel data studies in Spain, the Netherlands and South Africa (Edney et al 2022). England has been examined in particular detail, using cross-sectional instrumental variable studies of variation in health expenditure among many sub-national administrative areas – usually about 150 or more (Claxton et al 2015; Claxton et al 2018a; Lomas et al 2019; Martin et al 2021; Martin et al 2022; Longo et al 2023; Martin et al 2023). Early studies used census-based socioeconomic variables to instrument expenditure, but the well-established current approach is to use "funding rule" instruments which exploit quasi-exogenous variations in expenditure due to quirks in the sub-national funding formula (Andrews et al 2017). Findings have been broadly comparable between all studies: estimated all-age all-cause mortality elasticities typically range from about 0.5 to -1.5, with elasticities consistently above this in some disease areas (eg circulatory disease) and below in others (eg cancer) (Claxton et al 2018b; Martin et al 2021). Estimates have been found to be robust to changes in geography, identification strategy, sensitivity analysis of the validity of instruments used for identification, and comparison of disease area mortality with all-cause mortality (Claxton et al 2024). Effects are also comparable between total healthcare expenditure and secondary care expenditure, though the effect of public health expenditure (ie preventive services beyond healthcare) is found to be considerably greater per pound spent (Martin et al 2020).

However, only a handful of studies have examined how mortality effects vary between more and less socially advantaged groups. One study used an indirect approach that combined data on overall inpatient hospital utilisation by neighbourhood deprivation with previous estimates of mortality effects by broad disease categories (Love-Koh et al 2020). Two studies used a large area instrumental variable approach and navigated the challenges of sample size using quantile regression (Hernandez-Villafuerte et al 2022; Martin et al 2022). Finally, two studies used a time series approach that examined changing patterns of expenditure and mortality across large administrative areas with different levels of deprivation (Barr et al 2014; Currie et al 2019). These studies all concluded that the mortality effect per unit of marginal healthcare expenditure is larger in more deprived (or higher mortality) large area populations – implying that marginal increases in healthcare expenditure will tend to reduce health inequality. However, these studies were all vulnerable to potential biases that we address in this study, as explained below and in the Discussion section, and were all conducted in the 2000s and 2010s, prior to the sustained period of deterioration in the UK economy and public services during the 2010s. Furthermore, the quasi-experimental studies only looked at variations between large areas with heterogenous populations, which risks masking important effects on health inequality within those areas (Stafford et al 2008; Prouse et al 2014). Even if the large area findings were correct, it does not necessarily follow that deprived small areas benefited more from increases in healthcare expenditure than affluent small

areas. Most health inequality occurs within rather than between large administrative areas, and so studies that do not look at small area inequalities potentially miss the most important part of the picture (Stafford et al 2008).

This is the first study to estimate the causal effect of health care expenditure on social inequality in health using quasi-experimental methods based on small area level data on deprivation and mortality. We use the same well-established instrumental variable approach used in numerous studies of the overall mortality effects of health expenditure in England but innovate by estimating sub-group differences by deprivation and mortality at the small area level as well as the large area level. We also use more robust methods than previous large area quasi-experimental studies of the social gradient in mortality effects by: (1) focusing directly on health care expenditure, unlike previous time series studies which risk confounding by non-health care expenditure trends, (2) focusing directly on deprivation quintiles rather than mortality quintiles, unlike previous large area quantile regression studies, (3) using actual NHS expenditure geography rather than indirect mapping to local authority geographies, and (4) following Brindley et al (2023) in using only a single funding rule instrument, known as the "Distance from Target Index", which generates quasi-exogenous variation in funding based on historical factors unrelated to the need for secondary care expenditure. We believe that this is a more robust instrumental variable approach than those used in the two previous studies of this kind, one of which used census-based socioeconomic variables as instruments and one of which inappropriately used funding rule components related to the need for secondary care as instruments rather than control variables. As explained in detail in Methods section 4.1, we believe that need factors should be treated as controls rather than instruments, since they are causally linked to the outcome (mortality) as well as to the exposure (expenditure). We also report extensive diagnostic tests and sensitivity analysis.

We use a small area level of analysis for mortality outcomes and a large area level of analysis for health expenditure inputs. The large area level is appropriate for analysing expenditure, because this is the level at which expenditure is actually allocated within the English NHS. The small area level is more appropriate for analysing mortality effects by deprivation group, however, because this is the outcome of interest from a health inequality perspective. We focus on secondary care expenditure (which we sometimes refer to as "hospital" expenditure, for short) because this is the largest component of health expenditure in England (Brindley et al 2023) and may potentially have more immediate effects on mortality than primary care and public health expenditure focused on long-term prevention.

Our findings challenge the conventional wisdom that the poor always gain more from marginal increases in public expenditure on secondary care. Instead, we found that the middle deprivation group gained the most in our specific setting of England in 2018. Importantly, however, we did not examine the effects of a marginal increase in public expenditure on primary care and public health, which may tend to have a more "pro-poor" pattern of impacts than secondary care. Our findings also challenge the conventional wisdom that there is a "pro-poor" gradient in the health opportunity costs of introducing cost-increasing technologies and programmes into universal publicly funded health services, whereby more socially disadvantaged groups bear a larger share of the health opportunity costs.

2. Conceptual Framework

This section describes the main causal mechanisms that might plausibly generate differential mortality effects of marginal secondary care expenditure among different social advantage groups. In line with previous empirical findings, our tentative prior hypothesis was a “pro-poor” gradient – that is, a monotonic positive relationship between mortality effect and deprivation, with larger mortality effects in more deprived groups. A causal mechanism that would generate this pattern is diminishing marginal returns to additional expenditure on secondary care relative to need. In high income countries with universal health systems, a “disproportionate care law” operates whereby socially disadvantaged people tend to receive a smaller proportion of the secondary care they need than socially advantaged people, especially in terms of elective care (Cookson et al 2021). Socially advantaged people thus receive more “need adjusted” expenditure than socially advantaged people, where "need adjusted" expenditure is the proportion of needed expenditure received multiplied by mean per capita expenditure. If there are diminishing marginal returns to "need adjusted" expenditure, then the same increase in mean per capita expenditure will produce a smaller mortality gain for socially advantaged people than socially disadvantaged people.

However, three other mechanisms could generate a more complex pattern of effects. First, there may be a “sharp elbows” mechanism that influences how increases in the mean per capita secondary care funding available to a large area are shared out among individual patients living within that large area. Most of the additional expenditure is likely to go on elective outpatient and inpatient activity, and emergency activity might conceivably even fall if emergencies are prevented. Yet socially disadvantaged people may be less adept than socially advantaged people at seeking and demanding secondary care activity. Second, there may be a “crowding out” mechanism whereby public expenditure crowds out private expenditure on secondary care for the most socially advantaged, having little impact on their overall (public plus private) expenditure and outcomes. Third, there may be a “co-morbidity and co-investment” mechanism influencing the long-term health benefits of health care expenditure, whereby disadvantaged populations have worse health outcomes per additional unit of publicly funded secondary care expenditure than affluent populations. This is because socially disadvantaged populations tend to have greater co-morbidity and lesser ability to co-invest their own resources in health improvement alongside the publicly funded health care inputs, for example by adhering to medication and rehabilitation regimes, providing healthy living and working conditions conducive to recovery, helping to share information and coordinate health care inputs provided by different health care staff, and topping up publicly funded care where necessary through privately funded care.

There is currently no well-developed theory about what patterns to expect in what contexts, so our aim was to examine the effects empirically in the context of England in 2018.

3. Data

3.1. Secondary care funding allocations data

We used data on health care funding allocations in the financial year 2018/19 (England NHS 2018) to 195 NHS administrative areas in England, known as "Clinical Commissioning Groups" (CCGs), with responsibility for purchasing and planning secondary care for their local populations; the data were accessed from https://www.england.nhs.uk/allocations/ (accessed 20 April 2023). We focused on the main funding stream, known as “Core Allocations”, of which approximately two-thirds is assigned to general and acute hospital care (England NHS 2016). We excluded two separate funding streams for “Primary Care” and “Specialised Services”; the latter involves unusual conditions with high costs for individual patients and few providers. In 2018/19 “Core Allocations” represented 75% of CCG funding, while “Primary Care” and “Specialised Services” accounted for 8% and 17%, respectively (Brindley et al 2023).

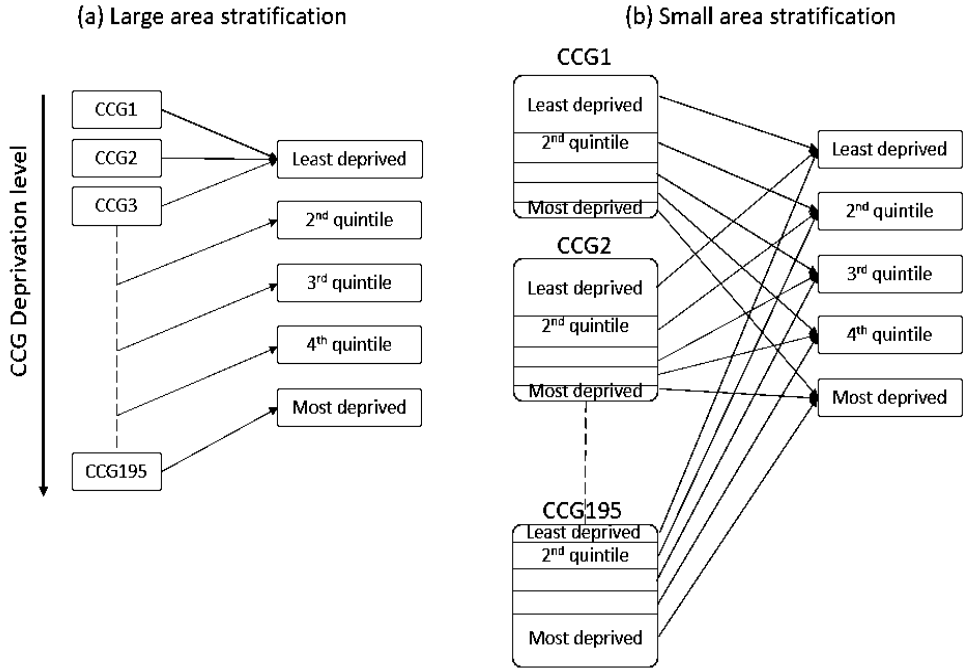
3.2. Population and mortality data

Our analysis employed mid-year population estimates for 2018 and data on deaths by sex and age [in 5-year bands from 0-4 to 90+] for the calendar year 2018 in England, both freely available from the Office for National Statistics (ONS) (Office for National Statistics 2019, 2020). Population estimates can be accessed from the ONS website (Office for National Statistics 2019, 2020), and mortality data is also available (accessed 30 March 2022). Our mortality data period (calendar year 2018) does not precisely overlap with our funding data period (financial year 6 April 2018 to 5 April 2019). However, that discrepancy is not material to our conclusions since our cross-sectional instrumental variable approach aims to estimate the steady-state annual mortality effect of a persistent medium-term change in annual expenditure over several years. Information on population and deaths is provided by 2011 Lower Layer Super Output Areas (LSOA), which are small areas with a mean population of about 1,700 and a minimum threshold population of 1,000. Our sample of 32,844 LOAs covers a population of 55,977,178 with 513,422 deaths recorded.

We linked the population and death data with the 2019 English Indices of Deprivation, which measure relative deprivation across English LSOAs (Noble et al 2019) available from the Ministry of Housing Communities and Local Government (Accessed 20 March 2022). England is a country with strong social segregation by housing, in which small area deprivation is a well validated measure of social status. Whole population data on individual level tax records linked to individual level mortality are not available in the UK. Thus, we use deprivation measured at LSOA small area instead. We use the overall index at LSOA level to construct deprivation quintile groups. This distinguishes our work from the existing literature (Barr et al 2014; Currie et al 2019; Love-Koh et al 2020; Hernandez-Villafuerte et al 2022; Martin et al 2022), which uses a large area (CCG) measure of deprivation. We link LSOAs with their corresponding CCGs using the official NHS technical guide codes that are publicly available, which also accounts for changes in CCGs over time (England NHS 2019).

We conducted sensitivity analysis at the CCG level, but our preferred level of analysis was the LSOA level, with deprivation and mortality varying by LSOA and large area funding allocation taking the same value across all LSOAs within the same CCG. Differences in funding between CCGs then generate differences in funding between small area deprivation groups within England, though not within any individual CCG. This small area stratification allowed us to measure the effect of the large area allocation on mortality across different small area deprivation groups, regardless of whether they reside in an affluent or deprived large area CCG, as shown in Figure 1.

Figure 1: Small area versus large area stratification



Notes: Large area stratification creates groups of large areas (CCGs) based on large area deprivation. Small area stratification creates groups of small areas (LSOAs) based on small area deprivation.

3.3. Outcome measures

The main outcome of interest was the age/sex standardised all-age mortality rate, calculated separately for each LSOA. There are 32,844 LSOAs in England, but we only use 32,784 of these in our regression estimates since we dropped 60 LSOAs with zero death counts in 2018 (0.18 of 1% of the total) before taking the logarithm of mortality. We used direct standardisation, with the 2018 English population as the base. In sensitivity analysis, we also examined life years lost per 100,000 general population under the age of 75, another measure commonly used in this literature. Reporting both outcomes facilitates comparison with other studies.

Table 1 shows descriptive statistics (mean and standard deviation) for hospital expenditure and the two mortality measures at the England level, by five small area deprivation quintile groups and both small area (LSOA) and large area (CCG) units of analysis.

Table 1: Main variables of interest by large and small area deprivation group

	Large area unit of analysis			Small area unit of analysis		
	Hospital expenditure per capita	Adjusted mortality rate per 100,000	Life years lost per 100,000	Hospital expenditure per capita	Adjusted mortality rate per 100,000	Life years lost per 100,000
Least deprived	1,170	806	3,259	1,218	777	2,721
2nd quintile	1,223	884	3,738	1,246	877	3,193
3rd quintile	1,296	928	4,131	1,255	962	3,761
4th quintile	1,298	949	4,287	1,270	1125	4,527
Most deprived	1,373	1069	5,029	1,310	1379	6,211
Overall	1,272	927	4,089	1,260	1,024	4,084

Notes: The deprivation quintile groups are stratified by 195 large NHS administrative areas CCGs and 32,784 small area LSOAs, respectively. The adjusted mortality rate is per 100,000 population, adjusted for age and sex, and the years of life lost are calculated for under age 75 per 100,000 population.

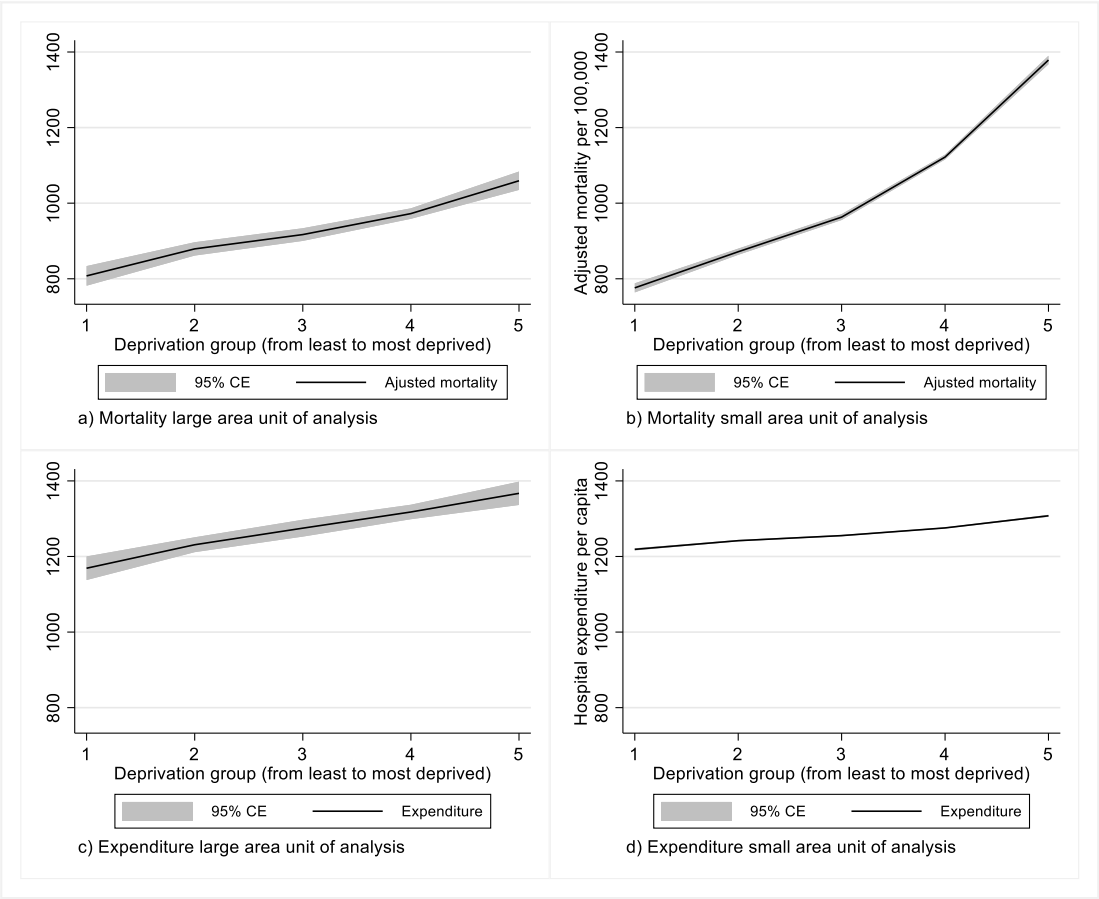
At large area level (CCG), we observed a steeper social gradient in hospital expenditure but a shallower social gradient in mortality. The most deprived quintile group of large areas received £1,170 British pounds per person, rising to £1,373 in the most deprived group. Whereas there were 1,069 deaths per 100,000 in the most deprived group of large areas compared to 806 in the least deprived. Similarly, there were 3,259 life years lost per 100,000 for the least deprived group of large areas, rising to 5,029 for the most deprived group. Large area analysis produces a shallower social gradient in mortality because aggregation from small to large area level averages out much of the small area variation in both mortality and deprivation.

At the small area level, by contrast, we observed a shallow social gradient in (age-unadjusted) hospital expenditure but a steep social gradient in (age-adjusted) mortality. Deprived small areas are contained in large areas that receive only slightly higher hospital expenditure, with £1,218 British pounds per person in the least deprived quintile group up to £1,310 in the most deprived.

Deprivation and age were negatively correlated, so the additional healthcare expenditure needs of deprived populations tended to be attenuated by their relative youth. In contrast, more deprived small areas had substantially higher age-adjusted mortality than less deprived ones, with 1,379 deaths per 100,000 for the most deprived compared with only 777 for the least deprived. For the most deprived small areas we observed 6,211 life years lost per 100,000, compared with 2,721 for the least deprived.

Figure 2 visualises these social gradients, showing the relationship between age-standardised mortality, hospital expenditure and deprivation quintile group by large and small areas of analysis, including 95% confidence intervals based on fractional-polynomial prediction. There are substantial differences between expenditure and mortality patterns at large and small area levels, and the confidence intervals are smaller at small area level due to increased statistical precision. This suggests that taking a fine-grained look at small area deprivation has the potential to reveal mortality effects that might otherwise remain hidden by large area aggregation.

Figure 2: Social gradient in hospital expenditure and mortality by large and small area stratification



Note: Fractional-polynomial prediction plots with 95% confidence interval for adjusted mortality on deprivation quintiles in panels a) and b) for large and small area unit of analysis, respectively, and for health expenditure per capita on deprivation quintiles in panels c) and d) for large and small area unit of analysis, respectively.

3.4. Control variables

We included control variables that we consider to be confounding factors that are causally linked with both our exposure (large area expenditure) and our outcome (small area mortality). As explained below, our preferred specification uses large area level controls for two components of the funding formula related to the need for hospital expenditure. We also use small area level controls for all six domains of the Index of Multiple Deprivation (IMD) 2019 other than health, ie education, barriers to housing, environment, employment, income, and crime domain scores. Previous studies (Andrews et al 2017; Claxton et al 2018a) have tended to use census variables as controls rather than IMD domain variables (which are based on both census and other variables), but have also found that the choice of data source for the control variables makes little difference. We did not include the health domain, since this is a proxy for both morbidity and mortality and would risk under-estimating the mortality effect due to over-adjustment (insofar as morbidity lies on the causal pathway from expenditure to mortality) and circularity (insofar as we would be adjusting mortality by mortality). However, we include it in sensitivity analysis.

We also conduct sensitivity analysis around using the IMD domains as large area level controls. There is room for debate about which level is more appropriate, since the small area level measures the small area mortality aspect of confounding more accurately, whereas the large area level measures the large area expenditure aspect more accurately.

4. Methods

We are interested in the causal relationship between secondary care funding allocation and mortality. We estimate this using a well-established cross-sectional instrumental variable (IV) approach that has been developed and refined in numerous previous studies (Andrews et al 2017; Claxton et al 2018a; Martin et al 2021; Brindley et al 2023).

A naïve regression equation (without IV) to estimate the overall marginal effect of allocation on mortality would take the following form:

$$Y_{ij} = \beta_0 + \beta_1 E_j + x'_{ij}\beta_2 + \epsilon_{ij} \quad (1)$$

with the dependent variable Y_{ij} denoting the log of the outcome (eg age-sex standardised mortality rate per 100,000) for LSOA i $(i = 1, \ldots, 32{,}784)$ in large area j and E_j the log of the allocation of hospital expenditure per capita in j. x_{ij} is a vector of control variables at LSOA level and ϵ_{ij} is the error term.

However, the variable E_j is potentially endogenous as funding allocations are influenced by need factors such as morbidity, which are also correlated with mortality. This introduces endogeneity into the relationship between funding and mortality, meaning that cross-sectional associations capture not only the effect of healthcare funding on health outcomes but also the reverse effect of health outcomes on healthcare funding. To address this endogeneity, we instrumented hospital funding using a component of the funding formula, known as the *Distance from Target Index (DfT)*, as explained later. The revised regression equation to estimate the overall effect on mortality takes the following form:

$$Y_{ij} = \beta_0 + \beta_1 \hat{E}_j + x'_{ij}\beta_2 + \epsilon_{ij} \quad (2)$$

where $\hat{E}_j$ is the log of the instrumented allocation of hospital expenditure from a first stage regression, $E_{ij} = \lambda_0 + \lambda_1 Z_j + x'_{ij}\lambda_2 + \omega_{ij}$, where Z_j is the distance from target instrumental variable and $\boldsymbol{x_{ij}}$ the same set of control variables.

We estimated both equations using a standard two-stage least squares method, with robust standard errors clustered by CCG because health expenditure is allocated at CCG level (Abadie *et al* 2023). Our main parameter of interest, β_1, is the elasticity of mortality with respect to expenditure allocation (ie the % change in mortality for a 1% change in expenditure). We prefer a log-log functional form because both mortality and expenditure are closer to log normal than normal in distribution, but we also report results using linear-linear, log-linear and linear-log forms. With the linear-linear form, β_1 estimates the absolute change in mortality for a £100 change in per capita expenditure after rescaling expenditure into units of £100 for convenience.

4.1. Strength of the Instrumental Variable

We use the so-called "funding rule" instrumental variable (IV) approach, based on quirks of the NHS funding formula that induce quasi-exogenous large area variations in expenditure. This is a well-established approach that has been used in a large body of empirical work in England for the past decade (Andrews et al 2017; Lomas et al 2019; Martin et al 2021; Martin et al 2022; Brindley et al

2023). This IV approach was introduced by Andrews and colleagues (Andrews et al 2017), who used theoretical simulations as well as empirical tests to argue that funding rule instruments should not be supplemented with less informative secondary IVs based on socioeconomic characteristics, as this tends to bias estimates downwards. The NHS core allocation target funding formula can be written as follows, where in its original form each index is set to a mean value of 1 across all the NHS planning areas:

(1) *Target budget per head = England budget per head × Age-Cost Index × Additional Needs Index × Market Forces Factor Index*

(2) *Actual budget per head = Target budget per head × Distance from Target Index*

The target budget is based on various factors indicating the relative need of each planning area. The actual budget is then adjusted using the "Distance from Target Index" (DfT) to reduce the pace of change in expenditure and avoid large and unexpected fluctuations in budgets, so that planning areas move towards their target budget in small steps rather than giant leaps. This index is based on the difference between the formula target and the historical allocation, and means that planning areas can be persistently "above" or "below" target for many years (Andrews et al 2017; Martin et al 2022). The Age-Cost Index is the main index of need for health care expenditure, based primarily on the age, sex and morbidity profile of the CCG as measured by a detailed set of person-level hospital diagnosis codes. This index is parameterised using detailed person-level regression modelling of expenditure patterns for all NHS hospital patients in England, based on the assumption that, on average, patients receive the care they need. The Additional Needs Index, based on avoidable mortality under age 75, is designed to adjust both for violations of this assumption (known as "unmet need") and additional concerns for reducing health inequality. The Market Forces Factor Index (MFF) accounts for geographical variation in local health care wages and input prices since areas with lower wages and prices have correspondingly lower need for expenditure.

A valid instrument needs to satisfy two main requirements: (1) the relevance condition, that it influences secondary care funding (ie the instrumented variable), and (2) the exclusion restriction, that it influences mortality (the outcome) only via secondary care funding and is uncorrelated with unobserved variables that may also influence mortality. The Additional Needs Index obviously does not meet the exclusion restriction since it is based directly on mortality. Several previous studies have therefore used three of these indices as candidate instruments – Age-Cost Index, MFF and DfT. More recently, however, it has been argued that the Age-Cost Index and MFF do not meet the exclusion restriction because they are causally linked to mortality, and so DfT should be employed as the sole instrumental variable (Brindley et al 2023). In addition, we believe that MFF does not actually meet the relevance condition, as explained below.

We start with the positive case for DfT, before making the negative case against Age-Cost Index and MFF. The relevance condition for DfT can be formally tested. Table 2 reports the results of the first-stage regression for our preferred model (small area stratification, small area controls, log-log functional form). This shows that DfT exhibits a statistically significant effect on hospital spending. The Kleibergen-Paap test for under-identification confirms that DfT is a strong predictor of hospital spending (p-value 0.000), with a first-stage F-statistic exceeding 106—comfortably above the conventional threshold of 10—thereby avoiding the "weak instrument problem" (Stock & Yogo 2002). These findings confirm that DfT is a strong predictor of health expenditure allocation. Moreover, the Hausman test indicates that hospital spending is endogenous (p-value = 0.000), which suggests that the ordinary least squares (OLS) regression is biased and justifies the use of an instrumental variable approach.

Table 2: First stage regression model
(outcome: natural log of hospital expenditure per capita)

VARIABLES	(1) Coef	(2) SE
Instrumental variable		
Natural log of Distance from Target Index	0.719***	0.070
Deprivation		
Least deprived	-0.024***	0.005
2nd quintile	-0.021***	0.004
3rd quintile	-0.020***	0.003
4th quintile	-0.012***	0.002
Most deprived	Ref.	Ref.
Control variables		
Lacking Education (score 0 to 100)	-0.089***	0.014
Lacking Employment (proportion 0 to 1)	9.832***	3.712
Poor Living Environment (0 to 100)	-0.006	0.013
Barriers to Housing and Services (0 to 100)	-0.086***	0.015
Risk of Crime (z-score in sd units, -4 to +4)	0.956***	0.256
Low Income (proportion 0 to 1)	6.586*	3.446
Market forces factor index	0.533***	0.084
Age-cost index	0.756***	0.040
Constant	5.878***	0.120
Observations	32,784	32,784
First-stage F stat	106.3	
Kleibergen-Paap test for relevance	p-value<0.001 H_0: IV is weak	
Hausman test for endogeneity	p-value<0.001 H_0: Spending is exogenous	

*Notes: Robust standard errors clustered by CCG. *p<0.10, **p<0.05, ***p<0.01. This is linear regression with a log-linear functional form, based on the natural logarithm of the outcome, which shows the percentage point change in hospital expenditure per capita for a one-unit change in the covariate. The Distance from Target Index has mean 0 and range -0.05 to 0.30 where the units represent proportional distances from target (eg 0.30 represents 30% above target). The original DfT variable is right-skewed with a long right-hand tail of CCGs with substantial distance from target. For linear estimation purposes, we re-scale this explanatory variable to yield a more symmetric distribution by adding 1 so that units represent shares of target (eg 1.30 represents 130% of the target share) and taking the logarithm. Deprivation groups are indicator variables taking the values of 0 or 1, Employment and Income are proportions from 0 to 1, Education, Living Environment and Barriers to Housing and Services are scores from 0 to 100, Crime is a z-score with mean value 1 and range about -4 to +4.*

There is no formal test to verify the exclusion restriction, so we must rely primarily on causal inference reasoning. DfT is used to implement a "pace of change" policy designed to avoid overly rapid changes in expenditure. It estimates how far the current funding differs from the target funding allocation based on assessed need only (ie all the other components of the formula). Planning areas that are substantially below target – ie historically “under-funded” – receive less than the full needed increase, and vice versa. Over time, this smooths out the funding shifts so that planning areas gradually move towards their target allocation in small steps rather than giant leaps. DfT thus captures historical influences on expenditure, which are distinct from all the need factors incorporated in the main part of the formula – including the need factors used in previous years as well as the need factors used this year. These historical influences may not be quasi-random, in the sense that they may be systematically determined by political and sociological processes. However,

they are at least quasi-exogenous, in the sense that they involve historical factors unrelated to need that are unlikely to exert any direct causal influence on mortality.

Following Basu (2014), we also test whether DfT is correlated with observable confounding variables hypothesised to influence mortality, which might suggest an indirect impact on mortality through other channels. This diagnostic information is reported in Appendix Table A1 along with information on the Age-Cost Index and MFF, in the form of linear regressions of IVs against control variables. Our results indicate that DfT is less strongly correlated with confounding variables than Age-Cost Index and MFF. We acknowledge that some correlation of DfT with confounding variables exists. However, we argue that DfT is conditionally exogenous once we control for these confounding factors in our regression.

Finally, we turn to the case against Age-Cost Index and MFF. The theoretical case against including the Age-Cost Index is that it is partly based on morbidity, which is likely to influence mortality directly. One theoretical argument against MFF is that it does not really meet the relevance condition, after all, since it only influences nominal expenditure but not real (local price-adjusted) purchasing power. Errors in the MFF adjustment might generate quasi-exogenous variation in real purchasing power, but we do not observe this error directly. An area with above-average MFF might actually have above-average prices, rather than this necessarily indicating a positive MFF measurement error. Another theoretical argument against MFF is that high wages and prices are an indicator of an economically successful metropolitan area, which might cause lower mortality via migration effects whereby healthy and high-skill workers migrate to metropolitan areas. Appendix Table A1 shows that Age-Cost and MFF are both strongly correlated with confounding variables expected to influence mortality, such as the Income domain of the index of multiple deprivation. This supports the theoretical argument that they are correlated with mortality through wider channels than hospital funding. We therefore use DfT as a sole instrument and the Age-Cost Index and MFF as control variables in our preferred specification, but report sensitivity analysis including Age-Cost Index and MFF as instruments in Appendix Table A6.

4.2. Sub-group analysis by deprivation group

To analyse the mortality elasticity for each deprivation group (also known as "conditional average treatment effects") we estimate the following specification:

$$Y_{ij} = \beta_0 + \beta_1 \hat{E}_j + \beta_2 (\hat{E}_j \circ q_{ij}^2) + \cdots + \beta_5 (\hat{E}_j \circ q_{ij}^5) + q_{ij}' \beta_6 + x_{ij}' \beta_7 + \epsilon_{ij} \quad (3)$$

where the instrumented allocation, $\hat{E}_j$, for large area j is interacted with four binary indicators of small area deprivation quintile group $q_{ij}^2, \ldots, q_{ij}^5$, with the reference category q_{ij}^1 (least deprived) dropped and deprivation group main effects included (using vector notation q_{ij} for all four deprivation indicators). This model augments our previous equation by assuming that small area mortality is a function of the interaction between expenditure and small area deprivation group, and of small area deprivation group, as well as large area expenditure and small area confounding factors.

In sensitivity analysis (Appendix Table A5), we also explore the possibility that the instrumental variable relationship between DfT and funding allocation may also interact with small area deprivation quintile group, by using five first-stage regressions, one to instrument expenditure (E_j) and four to instrument the interaction of expenditure with the deprivation quintile group, (($E_j \circ q_{ij}^2$), …, ($E_j \circ q_{ij}^5$)). As suggested by Wooldridge (2010), if Z_j is a valid instrument for E_j, then the

natural choice of additional instruments would be $((Z_j \circ q_{ij}^2), \ldots, (Z_j \circ q_{ij}^5))$. Then, the first first-stage equation takes the same form as before, except with the addition of deprivation group main effects and a set of interactions of deprivation with the instrumental variable, ie $E_j = \lambda_0 + \lambda_1 Z_j + \lambda_2 (Z_j \circ q_{ij}^2) + \cdots + \lambda_5 (Z_j \circ q_{ij}^5) + q_{ij}' \lambda_6 + x_{ij}' \lambda_7 + \omega_{ij}$, while the additional four first-stages follow the same pattern to instrument the interactions of expenditure with deprivation quintiles, ie $E_j \circ q_{ij}^k = \lambda_{0k} + \lambda_{1k} Z_j + \lambda_{2k} (Z_j \circ q_{ij}^2) + \cdots + \lambda_{5k} (Z_j \circ q_{ij}^5) + q_{ij}' \lambda_{6k} + x_{ij}' \lambda_{7k} + \omega_{ijk}, \forall\, k \in (2,..,5)$.

However, we prefer a single first-stage regression rather than this more flexible approach, as we have no specific theory or hypothesis about why our instrument (DfT) would have a different influence on expenditure among different small area deprivation groups.

The elasticity of mortality with respect to expenditure allocation to the first quintile group is the baseline expenditure coefficient $\xi_{Y,E|Q1} = \hat{\beta}_1$, where $\hat{\beta}_1$ is the two-stage least squares regression in equation 3. Similarly, $\xi_{Y,E|\mathrm{q2}} = \hat{\beta}_1 + \hat{\beta}_2, \xi_{Y,E|\mathrm{q3}} = \hat{\beta}_1 + \hat{\beta}_3, \ldots, \xi_{Y,E|q5} = \hat{\beta}_1 + \hat{\beta}_5$. In other words, the elasticity of mortality with respect to allocation for the second quintile is the sum of the first quintile elasticity (the dropped category) plus the coefficient on expenditure interacted with the second quintile, and similarly for the remaining quintiles.

We examined whether there is a significant pro-deprived or anti-deprived linear slope in mortality effects across deprivation groups by testing the null hypothesis $\hat{\beta}_1 + \hat{\beta}_2 = \hat{\beta}_4 + \hat{\beta}_5$, and we examined whether the middle group had a significantly larger effect than other groups by testing the null hypothesis $\hat{\beta}_3 > \frac{\hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_4 + \hat{\beta}_5}{4}$.

5. Results

5.1. Main results

Table 3 presents results using twelve variants of our preferred instrumental variable approach using Distance from Target Index (DFT) as the sole instrumental variable and a single first stage regression. We report variants using three different models – M1 large area stratification, M2 small area stratification with large area controls, and M3 small area stratification with small area controls – two different mortality variables – standardised all-age mortality and years of life lost under age 75 – and two different functional forms – log-log showing elasticities, and the linear-linear form showing absolute effects of £100 expenditure. Model M1 is our least preferred model, since this does not account for inequalities within large area stratification, and also, the statistical power is low with only 195 observations split into 39 observations per CCG quintile group. If forced to choose, we prefer M3 over M2, and full two-stage least squares results for this model in log-log form with all-age mortality as the outcome can be found in Appendix Tables A2 and A3. In the appendix, we also report results based on further variants in the choice of controls (Table A4) and different instrumental variable approaches (Table A5 and Table A6).

Table 3: Estimated coefficients for twelve main specifications

	Model 1		Model 2		Model 3	
	Large area unit of analysis (CCG)		Small area unit of analysis (LSOA) with GGC controls		Small area unit or analysis (LSOA) with LSOA controls	
	Estimate	SE	Estimate	SE	Estimate	SE
Outcome: Adjusted mortality elasticities (log-log)						
Least deprived	-1.068***	0.410	-1.138***	0.384	-0.879***	0.277
2nd quintile	-1.445***	0.422	-1.264***	0.393	-1.041***	0.293
3rd quintile	-1.299***	0.375	-1.265***	0.384	-1.010***	0.283
4th quintile	-1.149***	0.413	-1.151***	0.379	-0.935***	0.284
Most deprived	-1.116***	0.384	-0.764**	0.383	-0.758***	0.290
Overall	-1.215***	0.383	-1.116***	0.380	-0.925***	0.279
Flat slope test /1	-0.248	0.291	-0.487***	0.165	-0.228	0.169
Middle slope/2	-0.105	0.133	-0.186***	0.067	-0.107	0.066
Outcome: Adjusted mortality as absolute effect of £100 (linear-linear)						
Least deprived	-60.958***	23.560	-77.851***	24.536	-53.088***	16.672
2nd quintile	-83.861***	24.441	-78.484***	24.253	-54.606***	17.076
3rd quintile	-74.172***	20.834	-78.588***	24.353	-52.250***	17.330
4th quintile	-66.377***	23.419	-70.555***	24.190	-45.412**	17.639
Most deprived	-62.896***	20.988	-32.213	24.661	-20.463	18.694
Overall	-69.653***	21.189	-67.524***	23.985	-45.154***	16.913
Flat slope test /1	-15.546	19.830	-53.568***	12.137	-41.819***	12.556
Middle slope/2	-5.649	9.230	-13.812***	4.822	-8.858*	4.750

Table 3 (continued)

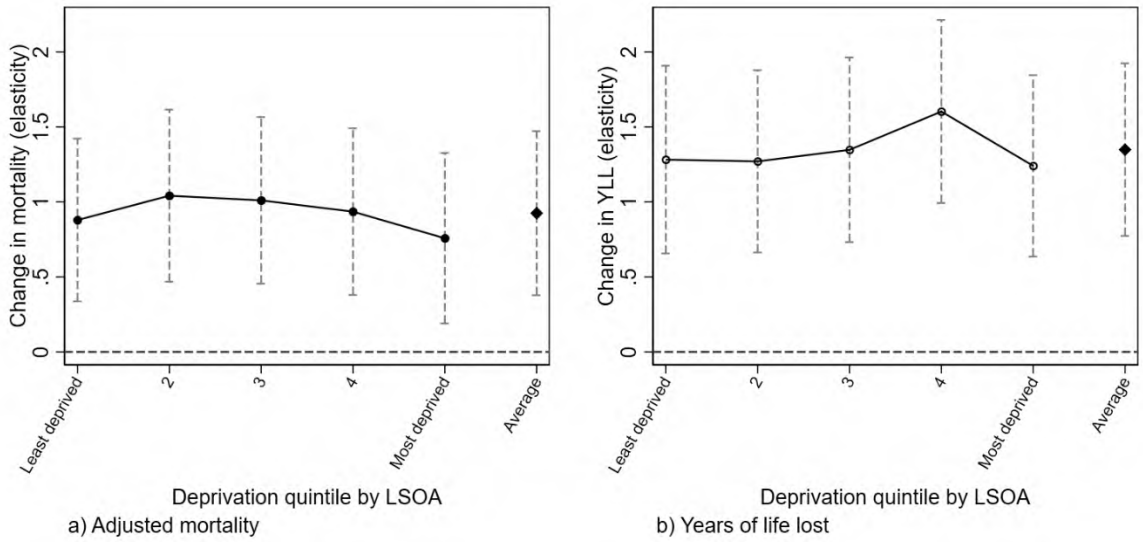
	Model 1		Model 2		Model 3	
	Large area unit of analysis (CCG)		Small area unit of analysis (LSOA) with GGC controls		Small area unit or analysis (LSOA) with LSOA controls	
	Estimate	SE	Estimate	SE	Estimate	SE
Outcome: Years of life lost elasticities (log-log)						
Least deprived	-1.029**	0.414	-1.460***	0.456	-1.282***	0.319
2nd quintile	-1.082***	0.403	-1.392***	0.437	-1.270***	0.310
3rd quintile	-0.960***	0.350	-1.491***	0.449	-1.347***	0.314
4th quintile	-1.020***	0.368	-1.630***	0.444	-1.602***	0.311
Most deprived	-0.691*	0.368	-0.759*	0.428	-1.240***	0.308
Overall	-0.956***	0.354	-1.346***	0.430	-1.348***	0.293
Flat slope test /1	-0.400	0.370	-0.463**	0.230	0.291	0.236
Middle slope/2	-0.005	0.167	-0.181	0.140	0.002	0.135
Outcome: Years of life lost as absolute effect of £100 (linear-linear)						
Least deprived	-328.68**	134.72	-432.65***	123.26	-333.83***	75.46
2nd quintile	-334.02**	129.85	-412.54***	118.25	-323.15***	73.31
3rd quintile	-274.13**	115.25	-439.09***	122.64	-354.67***	76.64
4th quintile	-286.99**	118.40	-436.62***	123.34	-398.31***	77.95
Most deprived	-159.55	108.37	-67.79	112.89	-220.82***	79.50
Overall	-276.67**	113.231	-357.62***	116.452	-326.12***	70.918
Flat slope test /1	-216.16*	116.674	-340.78***	69.721	-37.859	69.704
Middle slope/2	3.178	52.237	-101.69***	34.818	-35.640	34.524
Observations	195		32,784		32,784	

*Notes: Robust standard errors clustered by CCG. *p<0.10, **p<0.05, ***p<0.01. Estimated coefficients are marginal effects by deprivation group estimated by two-stage least squares with distance from target index (DFT) as the sole instrumental variable and expenditure interacted with deprivation quintile (full results for elasticities are reported in Appendix Tables A1 and A2, for adjusted mortality and life years lost, respectively); 1/ Flat slope test (least deprived + 2nd quintile) - (4th quintile + most deprived) = 0; 2/ Middle slope test: 3rd quintile - (least deprived + 2nd quintile + 4th quintile + most deprived)/4 = 0.*

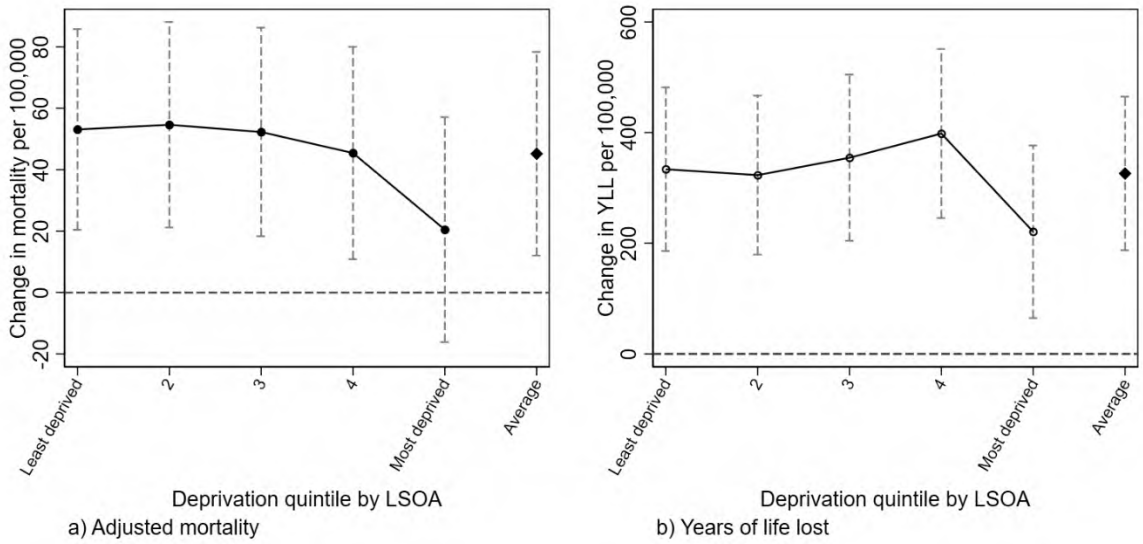
The overall effect is significant, and our preferred model shows that a 1% increase in expenditure reduces mortality by 0.92% [95% CI 0.37% to 1.47%]. The pattern of effects by deprivation quintile group exhibits an inverted U-shape pattern in all 12 variants, and the effect is significantly larger in the middle group in 10 out of 12 variants. However, there is no sign of a significant pro-poor gradient in any of the 12 model variants. We cannot reject the null hypothesis of no significant linear slope in 7 out of the 12 variants – ie the two most deprived groups gain the same as the two least deprived groups. Furthermore, in the other five variants, we find a significantly "pro-rich" slope – all four variants of model 2 and one variant of model 3 (mortality outcome, linear-linear form).

Figure 3: Mortality effect of hospital expenditure by small area deprivation group (four variants of preferred model 3)

(a) Elasticity



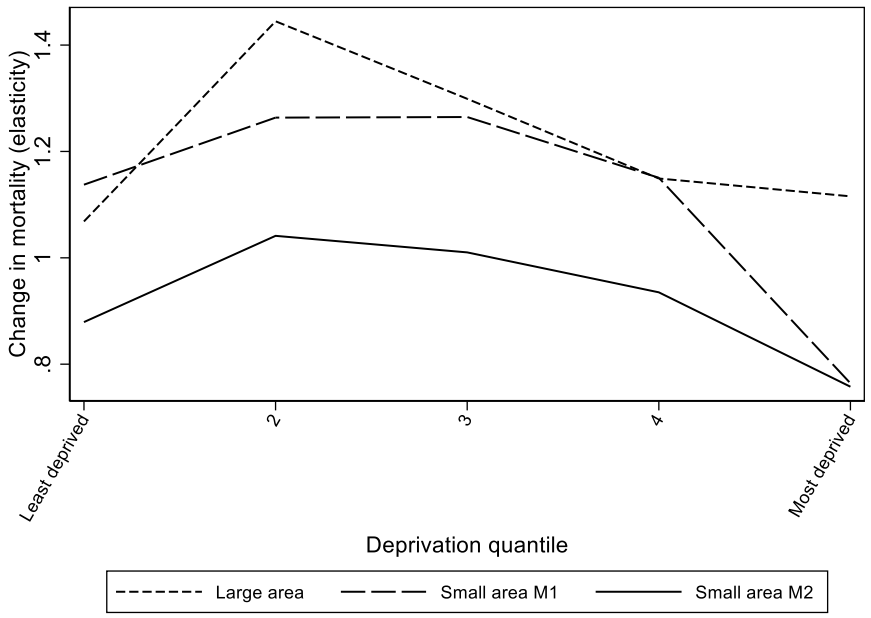
b) Absolute effect of £100 (linear-linear)



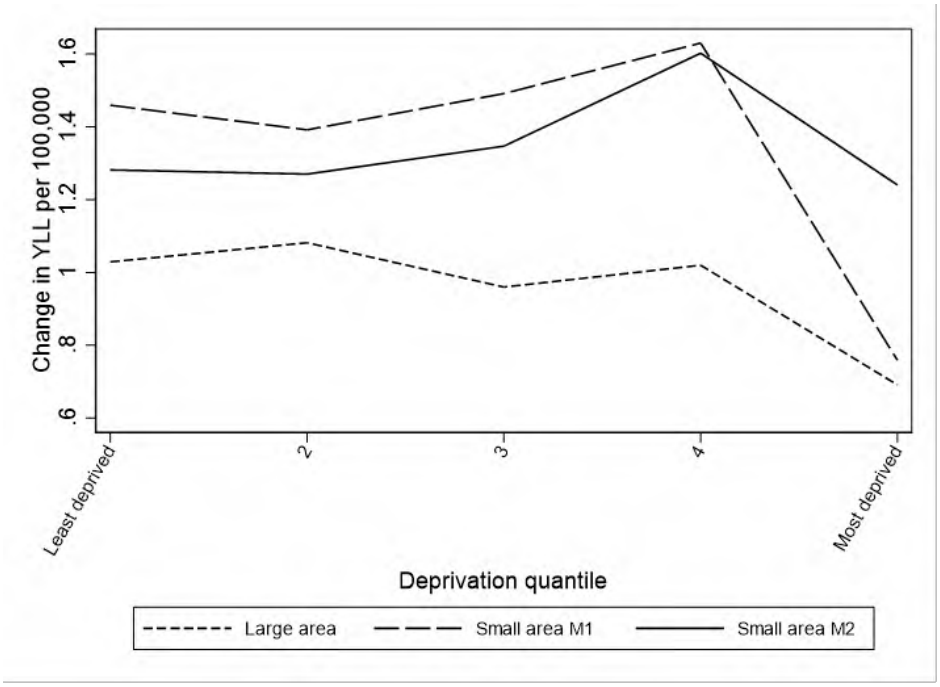
Note: To improve readability, we inverted signs. Our preferred specification is model 2 (small area stratification, small area controls). The elasticity shows the proportional effect on the mortality outcome of a 1% increase in hospital expenditure using a log-log specification, while the absolute effect shows the effect of £100 increase in expenditure using a linear-linear specification in terms of age-sex adjusted mortality per 100,000 and years of life lost under 75 per 100,000.

Figure 4: Comparison of social gradient patterns from all three main models (elasticity point estimates for mortality and years of life lost)

(a) Mortality



(b) Years of life lost



Note: This figure visualises the effect gradients reported in Table 3. "Large area" corresponds to Column 1, "Small Area M1" corresponds to Column 2, and "Small Area M2" corresponds to Column 3 of Table 3. The confidence intervals from Table 3 are not displayed here since this would clutter the graph and make it hard to visualise the basic patterns.

Figure 3 visualises the results for our preferred model 3, showing the inverted U-shape, where the third quintile group benefits more from marginal health expenditure. Figure 4 visualises the results for all three models, showing the same basic pattern in each case. Similarly, Figure A3 in the Appendix compares the preferred result with two additional specifications that incorporate five first stages, as shown in Appendix Table A5, further reinforcing our general findings.

5.2. Sensitivity Analyses

Sensitivity analyses around the IV approach are shown in Appendix Table A4, including a naïve regression with no IV, an expanded IV set with DfT, Age-Cost and MFF, and a reduced control set with only IMD domains as controls but not Age-Cost and MFF. The basic inverted-U pattern of effects is similar in all cases, though in the naïve and expanded IV set models none of the effects is significant, including the overall effect.

We also perform various other sensitivity analyses. Appendix Table A7 shows that excluding all controls sightly reduces the size of the effects but does not change the basic inverted-U pattern; and similarly with adding the IMD Health domain as a control. Appendix Figure A1 shows that using robust standard errors, rather than clustering small areas within CCGs, would yield smaller confidence intervals. Finally, our basic pattern of findings is robust to allowing for a different treatment effect for London (Appendix Table A8), change in functional forms to log-linear and linear-log specifications (Table A9 in the appendix), and using a “MFF-adjusted” NHS budget allocation per person to estimate the real purchasing power of the allocation (Table A10 in the appendix).

6. Discussion

6.1. Main Findings

We found that the mortality effect of a marginal change in public expenditure on secondary care in England in 2018/19 did not have a "pro-poor" pattern favouring more deprived groups but instead had a "pro-middle" pattern with an inverted-U shape, whereby the effect was larger in the middle deprivation group than in other groups. This basic pattern persisted whether effects were measured in proportional or absolute terms (ie log-log or linear-linear functional forms) and whether mortality was measured as an age-sex adjusted all-age mortality rate or as years of life lost under age 75. It was also robust to numerous sensitivity analyses. If anything, there was more sign of a "pro-rich" pattern than a "pro-poor" pattern, in that five of our twelve main specifications showed a significant "pro-rich" pattern.

This finding contradicted our prior expectation that more deprived people would gain more health from additional public expenditure on secondary care than less deprived people, due to diminishing marginal returns to additional expenditure on secondary care relative to need. It also contradicted the findings of previous quasi-experimental studies of the marginal effect of secondary care expenditure on mortality in England in the 2000s and early 2010s (Barr et al 2014; Lomas et al 2019; Love-Koh et al 2020; Martin et al 2022). Although we do not know the precise mechanisms involved, we speculate that three main mechanisms may be driving our results. First, a "sharp elbows" mechanism whereby more deprived groups may be less proactive in seeking access to improved elective inpatient and outpatient hospital services than other groups. Second, a "crowding out" mechanism whereby the least deprived group may gain smaller health benefits than other groups because increases in public expenditure may be crowded out by countervailing decreases in private expenditure for the richest, generating smaller net impacts on utilisation and outcomes. Third, a "co-morbidity and co-investment" mechanism whereby poorer groups may have worse health outcomes from hospital treatment than other groups, due to greater co-morbidity and lesser ability to co-invest their own private resources in care co-ordination, recovery in a healthy living environment, and compliance with long-term treatment regimes. These mechanisms may help to explain why the health benefits of incremental healthcare expenditure were larger in middle groups than the extremes.

6.2. Strengths and Limitations

The main strength of our study is the use of small area data on mortality and deprivation to estimate how the mortality effects of public expenditure vary between more and less deprived populations. This allows us to measure deprivation more precisely than previous studies using large area data, accounting for impacts on health inequality within large areas.

A second strength is that we use a well-established instrumental variable approach to allow for endogeneity bias, based on a quirk of the NHS funding formula that generates quasi-exogenous variation in funding, with careful theoretical discussion of the rationale for our chosen instrumental variable, careful empirical diagnostic checks, and extensive sensitivity analysis. A third strength is that we report findings for two different mortality outcomes to facilitate comparison with other studies – all-age age-sex standardised mortality and years of life lost under age 75 – and in two different forms useful for different policy purposes – ie both elasticities and absolute effects.

The main limitation is that our cross-sectional instrumental variable approach rests on causal inference assumptions that cannot be directly tested. We rely on the twin assumptions that our "Distance from Target" instrument reflects variation in expenditure that is both (i) quasi-exogenous and (ii) sustained. The former assumption has already been carefully justified in Section 4.1, together with extensive diagnostic checks. The latter assumption means that, like the authors of many

previous instrumental variable studies in this literature, we interpret our findings as the medium-term effect of a sustained change in annual expenditure on annual mortality rather than the short-term effect of a short-term change in expenditure in the current year only. That is why the slight discrepancy in time periods between our funding and mortality data (financial year and calendar year 2018, respectively) is not material to our conclusions. A second limitation is that we are not able to estimate effects on secondary care utilisation and expenditure at small area level, and we have no data on private expenditure. This means we cannot tell how far our results are due (i) how increases in funding to large planning areas are shared out between more and less deprived residents within those large areas (ie the "sharp elbows" mechanism), (ii) how changes in public funding influence private expenditure by less deprived groups (ie the "crowding out" mechanism), or (iii) how the health benefit of one pound's worth of additional secondary care varies between more and less deprived individuals (ie the "co-morbidity and co-investment" mechanism). However, this limitation does not bias or invalidate our main conclusion. We can safely conclude that, around the year 2018/19, people in the two most deprived quintile groups of small areas of England did not gain more health than those in other groups from increases in secondary care funding and did not lose more health from decreases.

6.3. Comparison with Existing Literature

Our findings appear to contradict those of five previous studies of English data from the 2000s to early 2010s, briefly described in the Introduction, all of which found that changes in secondary care expenditure tended to have larger mortality effects in more deprived or higher-mortality populations. It is possible this discrepancy is due to a structural change in the social patterning of hospital expenditure effects in England from pro-deprived to pro-middle by the late 2010s, due to substantial and sustained deterioration in economic growth, health care and wider public services in England since 2010 that may have strengthened all three mechanisms described above (ie "sharp elbows", "crowding out", and "co-morbidity and co-investment"). This deterioration plausibly had a disproportionate impact on health and living conditions among more deprived populations, resulting in even later diagnosis, even greater co-morbidity, and even less ability to co-invest in recovery, rehabilitation and relapse prevention. Supporting evidence for this speculation is that more deprived groups have tended to use disproportionately more emergency care and disproportionately less elective and outpatient care since the early 2010s (Stoye et al 2020b; England NHS 2024). If this structural change hypothesis is correct, there is little prospect of this social gradient switching back again any time soon since economic conditions and public services in England have deteriorated further since the late 2010s, following Brexit, the Covid-19 pandemic, the Ukraine war and the cost-of-living crisis, and are unlikely to improve rapidly in the coming decade.

However, it is also possible that all five previous studies were biased in favour of finding a pro-deprived gradient, especially the study by Love-Koh and colleagues (Love-Koh et al 2020). This study found that 26% of the total health effect from an expenditure shift would benefit the most deprived small area quintile group and only 14% to the least deprived. However, this study did not examine health outcomes directly. It relied on two questionable assumptions: (i) proportionality between average and marginal expenditure, and (ii) equal marginal productivity of health expenditure across deprivation groups. The first assumption is biased because the steep gradient found in the study was mostly driven by emergency utilisation (Asaria et al 2016; Stoye et al 2020a) – and if the study were repeated using more recent data, it would be entirely driven by emergency utilisation: the gradient in elective admissions reversed during the 2010s, from slightly pro-deprived in the early 2010s to slightly anti-deprived by the late 2010s (England NHS 2024). Additional expenditure is more likely to be spent on increasing the supply of elective and outpatient care than emergency care, and the impact on emergency admissions could conceivably even be negative if acute emergencies are prevented by improved elective care. Furthermore, more deprived individuals may be less able

proactively to seek discretionary increases in elective hospital care than less deprived individuals (Cookson et al 2021). The second assumption will also bias the study in favour of finding a pro-poor gradient. Deprived populations might have worse health outcomes per marginal unit of expenditure than affluent populations due to greater co-morbidity and lesser ability to co-invest in self-care (Cookson et al 2021).

Two large area studies used quantile regression to estimate effect sizes at different points in the distribution of the mortality outcome (Hernandez-Villafuerte et al 2022; Martin et al 2022), and both found that secondary care allocations had a greater proportionate effect in administrative areas with higher mortality rates. To shed light on this apparent discrepancy, we analyse our own data using a quantile regression approach in Figure A2 in the appendix, comparing small area and large area analysis. Unlike the two previous large area quantile regression studies, our quantile regressions show larger mortality effects in lower mortality areas – and this finding persists whether we use of small or large area level analysis. We believe that our instrumental variable regression approach is less biased than these two previous studies, since one of these studies used census-based socioeconomic variables as instruments rather than funding components, and one used the Age-Cost Index and Market Forces Factor as instrumental variables rather than control variables, which is inappropriate for reasons already described in detail in our Methods section.

Finally two previous studies used a time series approach, exploiting differential changes in expenditure in more and less deprived large areas to identify causation (Barr et al 2014; Currie et al 2019). They found that more deprived local government areas in England tended to experience larger changes in amenable mortality age under 75 than less deprived administrative areas per unit change in healthcare expenditure, both during the 2000s (a period of high healthcare expenditure growth) and the 2010s (a period of low healthcare expenditure growth). Our study does not necessarily contradict this finding, however, since we only look at the mortality effects of secondary care expenditure whereas these previous time series studies looked at total health funding allocations including primary care, public health and specialised care. It is also possible that the previous time series studies were confounded by the mortality effects of an even wider range of public expenditure changes – beyond the health system – since they looked at periods of pro-poor cross-government public expenditure changes during the 2000s which were explicitly aimed at reducing health inequality and improving life chances in deprived populations.

6.4. Conclusions and Policy Implications

Our main conclusion is that there is not currently a “pro-poor” social gradient in the mortality effects of changes in secondary care expenditure in England, whereby more deprived individuals gain substantially larger health benefits than less deprived individuals. This conclusion is specific to secondary care expenditure, and we cannot draw conclusions about the impacts of changes in primary care, public health, or social care expenditure on health inequality. It is also specific to England since the late 2010s since we cannot rule out the possibility of a structural shift in this gradient since the early 2010s due to deteriorating economic conditions and public services. Furthermore, we do not know the relative contribution of the three plausible mechanisms that may be generating this finding – ie (i) the “sharp elbows” mechanism relating to how far increases in hospital funding for large administrative areas of England are unequally shared between more and less deprived people living within those areas, (i) the “crowding out” mechanism relating to how far private expenditure on hospital care is crowded out by increases in public expenditure among the least deprived group, and (iii) the “co-morbidity and co-investment” mechanism relating to how far more deprived people gain less health per additional pound of hospital expenditure than less deprived people.

Our main conclusion is more robust than those of previous studies, especially the study by Love-Koh and colleagues, which estimated a steep and positive social gradient in health opportunity costs in

England based on implausible assumptions (Love-Koh et al 2020) and two quantile regression instrumental variable studies that found larger mortality effects of secondary care expenditure in higher-mortality large areas based on instrumental variable approaches that are less robust than those used in the current study (Hernandez-Villafuerte et al 2022; Martin et al 2022). Our conclusion is also more specific to secondary care than the conclusion of previous time series studies (Barr et al 2014; Currie et al 2019), which found larger mortality effects of changes in total health expenditure in more deprived large areas, and may also have picked up effects of changes in expenditure on wider public services.

Our findings have important implications for the conduct of distributional cost-effectiveness analysis (DCEA) of the health inequality impacts of new technologies and programmes. When conducting such studies, an assumption is needed about the social distribution of health opportunity cost. Our findings suggest that, at least in the case of England since the late 2010s, it is not appropriate to assume a steep monotonic gradient in health opportunity cost, whereby more deprived groups are assumed to bear a much larger share of health opportunity cost than less deprived groups. Instead, a more reasonable base case assumption for England may be a flat distribution with a 20% share in each group since there was no sign of a significant "pro-poor" gradient in any of our main specifications and although we did observe a slight "pro-rich" gradient in some specifications, this was not significant in 3 out of 4 variants of our preferred model. Assuming a flat gradient may be more appropriate than assuming a "pro-middle" pattern since (1) the precise magnitude and shape of the pro-middle pattern are highly uncertain, (2) in practice, a flat gradient will generally yield the same estimate of health inequality impact as a pro-middle pattern so long as the pro-middle pattern is symmetrical between the two most and least deprived groups, and (3) a flat gradient is a more parsimonious assumption. Given substantial uncertainty and conflicting evidence from different studies, however, it would be appropriate to conduct sensitivity analysis using alternative pessimistic and optimistic scenarios. For example, if a flat gradient is the base case assumption, a suitable "pessimistic" scenario yielding a smaller health inequality reduction might be a slight pro-deprived gradient (eg 22%, 21%, 20%, 19%, 18%, respectively, for the most to least deprived group) and a suitable "optimistic" scenario yielding a larger health inequality reduction might be the corresponding slight anti-deprived gradient (eg 18%, 19%, 20%, 21% and 22%, respectively).

Our findings also have the direct policy implication that reducing health inequality requires more than simply increasing total secondary care expenditure or simply re-directing secondary care expenditure towards large administrative areas with high average levels of deprivation. Additional efforts are needed to ensure secondary care is targeted and used more effectively to improve the health of socially disadvantaged individuals living within large administrative areas (Sutton & Lock 2000). Various policies might support this objective within local health systems, including identification of underserved individuals and neighbourhoods, re-prioritisation of resources to tackle diseases that are disproportionately prevalent among disadvantaged individuals, policies to facilitate earlier diagnosis of need for secondary care among disadvantaged people, along with more timely provision of secondary care including innovative forms of delivery, and provision of proactive care co-ordination services where needed to address specific needs. Finally, our findings also support the conventional wisdom that reducing health inequality requires wider action to prevent the need for secondary care by re-directing resources towards primary care, public health, and early intervention to tackle the wider social determinants of health.

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Appendix

Appendix Table A1: Regression of potential instrumental variables on controls

	Distance from Target		MFF		Age index	
	Coef	SE	Coef	SE	Coef	SE
Education	-0.236***	0.071	-0.426***	0.045	0.331***	0.077
Employment	81.792*	47.128	-180.062***	29.585	927.141***	66.579
Environment	0.031	0.048	-0.082***	0.030	0.129***	0.048
Housing	-0.058	0.066	0.212***	0.051	0.291***	0.098
Crime	0.504	1.016	4.916***	0.800	-7.719***	1.295
Income	-9.965	38.061	126.790***	23.877	-572.747***	51.770
Constant	-0.012	0.020	1.077***	0.019	0.658***	0.036
Observations	32,784		32,784		32,784	

*Notes. : Clustered standard errors in parentheses clustered by 195 CCGs. *** p<0.01, ** p<0.05, * p<0.1.*

Appendix Table A2: Full base case regression (DFT, log-log, small area stratification) adjusted mortality

	First stage		Second stage	
	Coef	SE	Coef	SE
Health expenditure (in log)			-0.758***	0.290
Deprivation				
Least deprived	-0.024***	0.005	0.526	0.753
2nd quintile	-0.022***	0.004	1.797**	0.729
3rd quintile	-0.021***	0.003	1.647***	0.612
4th quintile	-0.013***	0.002	1.216**	0.554
Most deprived	Ref.		Ref.	
Interaction deprivation health expenditure (in log)				
Least deprived x health expenditure			-0.122	0.105
2nd quintile x health expenditure			-0.284***	0.102
3rd quintile x health expenditure			-0.253***	0.086
4th quintile x health expenditure			-0.178**	0.077
Control variables				
Lacking Education (score 0 to 100)	-0.092***	0.015	-0.173***	0.055
Lacking Employment (proportion 0 to 1)	10.575***	3.683	27.189	19.966
Poor Living Environment (0 to 100)	-0.008	0.013	-0.120***	0.028
Barriers to Housing and Services (0 to 100)	-0.087***	0.015	-0.435***	0.046
Risk of Crime (z-score in sd units, -4 to +4)	0.938***	0.252	3.574***	0.622
Low Income (proportion 0 to 1)	6.521*	3.424	112.240***	16.931
Market forces factor index	0.539***	0.083	-0.181	0.221
Age-cost index	0.758***	0.040	0.670***	0.240
Instrumental variable				
Distance from target -DfT (in log)	0.583***	0.071		
Least deprived x IV	0.308***	0.086		
2nd quintile x IV	0.179***	0.053		
3rd quintile x IV	0.162***	0.051		
4th quintile x IV	0.097**	0.047		
Constant	5.872***	0.119	11.855***	1.723
Observations	32,784		32,784	

*Note: Clustered standard errors in parentheses clustered by 195 CCGs. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is slightly lower than the full set of 32,844 LSOAs because the logarithm specification eliminates observations with LSOA counts of zero in the outcome variable.*

Appendix Table A3: Full base case regression (DFT, log-log, small area stratification) YLL

	First stage		Second stage	
	Coef	SE	Coef	SE
Health expenditure (in log)			-1.240***	0.308
Deprivation				
Least deprived	-0.024***	0.005	-0.043	1.217
2nd quintile	-0.022***	0.004	0.012	1.194
3rd quintile	-0.021***	0.003	0.678	1.202
4th quintile	-0.013***	0.002	2.581**	1.082
Most deprived	Ref.		Ref.	
Interaction deprivation health expenditure (in log)				
Least deprived x health expenditure			-0.041	0.171
2nd quintile x health expenditure			-0.030	0.167
3rd quintile x health expenditure			-0.107	0.169
4th quintile x health expenditure			-0.362**	0.152
Control variables				
Lacking Education (score 0 to 100)	-0.092***	0.015	-0.125*	0.074
Lacking Employment (proportion 0 to 1)	10.576***	3.684	506.835***	29.989
Poor Living Environment (0 to 100)	-0.008	0.013	-0.146***	0.044
Barriers to Housing and Services (0 to 100)	-0.087***	0.015	-0.303***	0.061
Risk of Crime (z-score in sd units, -4 to +4)	0.937***	0.252	1.932*	1.042
Low Income (proportion 0 to 1)	6.521*	3.424	-83.497***	21.630
Market forces factor index	0.539***	0.083	-0.043	0.275
Age-cost index	0.758***	0.040	1.068***	0.260
Instrumental variable				
Distance from target -DfT (in log)	0.583***	0.071		
Least deprived x IV	0.310***	0.086		
2nd quintile x IV	0.178***	0.054		
3rd quintile x IV	0.162***	0.051		
4th quintile x IV	0.096**	0.048		
Constant	5.872***	0.119	11.855***	1.723
Observations	32,784		32,784	

Note: Same as in appendix Table A2

Appendix Table A4: Sensitivity to selection of control variables

	ESTIMATIONS AT CCG LEVEL						ESTIMATIONS AT LSOA LEVEL					
	6 IMD controls		6 IMD + MFF+ Age index		6 IMD controls at CCG level		6 IMD controls at CCG level +MFF+Age index		6 IMD controls at LSOA level		6 IMD controls at LSOA level + MFF + Age index	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Outcome: Adjusted mortality elasticities (log-log)												
Least deprived	-0.903*	0.469	-1.068***	0.410	-1.006***	0.341	-1.138***	0.384	-0.701**	0.305	-0.879***	0.277
2nd quintile	-1.348***	0.475	-1.445***	0.422	-1.160***	0.346	-1.264***	0.393	-0.899***	0.323	-1.041***	0.293
3rd quintile	-1.292***	0.442	-1.299***	0.375	-1.170***	0.336	-1.265***	0.384	-0.868***	0.305	-1.010***	0.283
4th quintile	-1.154**	0.472	-1.149***	0.413	-1.060***	0.331	-1.151***	0.379	-0.790***	0.305	-0.935***	0.284
Most deprived	-1.300***	0.453	-1.116***	0.384	-0.693**	0.328	-0.764**	0.383	-0.673**	0.305	-0.758***	0.290
Overall	-1.199***	0.445	-1.215***	0.383	-1.018***	0.331	-1.116***	0.380	-0.786***	0.302	-0.925***	0.279
Flat slope test /1	0.203	0.303	-0.248	0.291	-0.413**	0.170	-0.487***	0.165	-0.137	0.173	-0.228	0.169
Middle slope/2	-0.115	0.153	-0.105	0.133	-0.190***	0.066	-0.186***	0.067	-0.102	0.066	-0.107	0.066
Outcome: Adjusted mortality as absolute effect of £100 (linear-linear)												
Least deprived	-51.269**	25.702	-60.958***	23.560	-74.697***	22.247	-77.851***	24.536	-49.101***	18.440	-53.088***	16.672
2nd quintile	-77.035***	25.954	-83.861***	24.441	-77.446***	21.870	-78.484***	24.253	-54.251***	19.208	-54.606***	17.076
3rd quintile	-72.007***	23.255	-74.172***	20.834	-78.089***	21.829	-78.588***	24.353	-52.436***	18.799	-52.250***	17.330
4th quintile	-65.291***	24.914	-66.377***	23.419	-70.558***	21.590	-70.555***	24.190	-45.664**	19.157	-45.412**	17.639
Most deprived	-72.137***	23.328	-62.896***	20.988	-33.888	21.742	-32.213	24.661	-25.977	19.522	-20.463	18.694
Overall	-67.548***	23.095	-69.653***	21.189	-66.922***	21.390	-67.524***	23.985	-45.478**	18.474	-45.154***	16.913
Flat slope test /1	9.124	20.431	-15.546	19.830	-47.696***	12.408	-53.568***	12.137	-31.711**	13.029	-41.819***	12.556
Middle slope/2	-5.574	10.351	-5.649	9.230	-13.941***	4.842	-13.812***	4.822	-8.688*	4.785	-8.858*	4.750
Outcome: Years of life lost elasticities (log-log)												
Least deprived	-1.045**	0.522	-1.029**	0.414	-1.323***	0.445	-1.460***	0.456	-0.986***	0.353	-1.282***	0.319
2nd quintile	-1.228**	0.497	-1.082***	0.403	-1.294***	0.419	-1.392***	0.437	-1.007***	0.309	-1.270***	0.310
3rd quintile	-1.150**	0.490	-0.960***	0.350	-1.406***	0.434	-1.491***	0.449	-1.072***	0.330	-1.347***	0.314
4th quintile	-1.268***	0.487	-1.020***	0.368	-1.549***	0.429	-1.630***	0.444	-1.319***	0.324	-1.602***	0.311
Most deprived	-1.065**	0.482	-0.691*	0.368	-0.670*	0.406	-0.759*	0.428	-1.029***	0.329	-1.240***	0.308
Overall	-1.151**	0.474	-0.956***	0.354	-1.254***	0.413	-1.346***	0.430	-1.083***	0.310	-1.348***	0.293
Flat slope test /1	0.061	0.356	-0.400	0.370	-0.368	0.223	-0.463**	0.230	0.354	0.242	0.291	0.236
Middle slope/2	0.002	0.181	-0.005	0.167	-0.190	0.139	-0.181	0.140	0.014	0.134	0.002	0.135
Outcome: Years of life lost as absolute effect of £100 (linear-linear)												
Least deprived	-307.22**	138.58	-328.68**	134.72	-400.33***	117.82	-432.65***	123.26	-267.16***	80.79	-333.83***	75.46
2nd quintile	-347.19***	129.59	-334.02**	129.85	-389.04***	110.62	-412.54***	118.25	-265.78***	72.11	-323.15***	73.31
3rd quintile	-294.15**	126.05	-274.13**	115.25	-418.64***	114.51	-439.09***	122.64	-295.55***	76.99	-354.67***	76.64
4th quintile	-320.41***	121.99	-286.99**	118.40	-416.98***	114.82	-436.62***	123.34	-337.89***	77.99	-398.31***	77.95
Most deprived	-215.13*	110.69	-159.55	108.37	-52.02	105.27	-67.79	112.89	-178.46**	83.33	-220.82***	79.50
Overall	-296.82**	117.36	-276.67**	113.23	-335.29***	108.65	-357.62***	116.45	-268.94***	72.51	-326.12***	70.92
Flat slope test /1	-118.87	112.28	-216.16*	116.67	-320.37***	70.57	-340.78***	69.72	-16.58	70.76	-37.86	69.70
Middle slope/2	3.34	55.93	3.18	52.24	-104.04***	34.64	-101.69***	34.82	-33.22	34.18	-35.64	34.52
Observations	195		195		32,784		32,784		32,784		32,784	

*Note: Robust standard errors clustered by CCG. *p<0.10, **p<0.05, ***p<0.01. Estimated coefficients are marginal effects by deprivation group estimated by two-stage least squares with distance from target index (DFT) as the instrumental variable and expenditure interacted with deprivation quintile; 1/ Flat slope test (least deprived + 2nd quintile) - (4th quintile + most deprived) = 0; 2/ Middle slope test: 3rd quintile - (least deprived + 2nd quintile + 4th quintile + most deprived)/4 = 0.*

Appendix Table A5: Sensitivity to selection of control variables: analysis with five first stages

	ESTIMATIONS AT CCG LEVEL				ESTIMATIONS AT LSOA LEVEL							
	6 IMD controls at CCG level		6 IMD controls at CCG level +MFF+Age cost index		6 IMD controls at CCG level		6 IMD controls at CCG level +MFF+Age cost index		6 IMD controls at LSOA level		6 IMD controls at LSOA level + MFF + Age cost index	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Outcome: Adjusted mortality elasticities (log-log)												
Least deprived	-4.420	3.368	-3.861	2.737	-0.938**	0.424	-0.991**	0.412	-0.421	0.311	-0.644**	0.277
2nd quintile	-1.539	1.578	-0.900	1.390	-1.306**	0.513	-1.373**	0.540	-0.986**	0.478	-1.100***	0.423
3rd quintile	-1.419***	0.472	-1.272**	0.498	-1.418***	0.435	-1.472***	0.438	-1.183***	0.406	-1.270***	0.341
4th quintile	-0.354	0.449	-0.565	0.538	-0.815***	0.270	-0.925***	0.303	-0.731***	0.216	-0.847***	0.225
Most deprived	-0.728**	0.288	-0.867**	0.361	-0.646**	0.261	-0.839***	0.323	-0.602**	0.257	-0.761***	0.275
Overall	-1.692**	0.699	-1.493**	0.612	-1.025***	0.338	-1.120***	0.366	-0.784***	0.290	-0.924***	0.264
Flat slope test /1	-4.877	3.696	-3.329	2.757	-0.783	0.633	-0.599	0.572	-0.074	0.471	-0.136	0.451
Middle slope/2	0.342	0.947	0.276	0.887	-0.492	0.217	-0.440**	0.201	-0.498**	0.219	-0.432**	0.194
Outcome: Adjusted mortality as absolute effect of £100 (linear-linear)												
Least deprived	-293.396	224.280	-263.851	189.152	-59.734**	24.294	-62.287**	25.141	-23.119	16.233	-32.605**	15.451
2nd quintile	-91.142	104.072	-56.814	93.809	-66.367***	25.505	-69.412**	27.878	-44.295*	23.114	-44.999**	20.776
3rd quintile	-77.495***	25.038	-70.225***	26.587	-78.277***	26.295	-80.834***	27.642	-60.732***	22.940	-60.155***	20.282
4th quintile	-30.342	28.965	-42.190	34.262	-62.142***	20.787	-66.832***	23.462	-53.890***	18.668	-54.332***	18.441
Most deprived	-49.176***	18.897	-56.829**	23.361	-52.454**	24.627	-60.169**	29.131	-45.141*	26.512	-45.689	27.870
Overall	-108.310**	46.660	-97.982**	41.926	-63.790***	21.857	-67.903***	24.546	-45.436***	18.367	-47.556***	17.728
Flat slope test /1	-305.019	246.210	-221.646	191.186	-11.505	27.401	-4.697	25.868	31.618	29.029	22.417	28.779
Middle slope/2	38.519	60.859	34.696	57.813	-18.103	14.016	-16.159	13.576	-19.121	13.780	-15.749	13.069
Outcome: Years of life lost elasticities (log-log)												
Least deprived	-5.200	3.858	-4.040	2.727	-1.129**	0.520	-1.191**	0.494	-0.515	0.409	-0.913**	0.362
2nd quintile	-2.032	1.447	-0.953	1.017	-1.384***	0.480	-1.446***	0.476	-1.004***	0.310	-1.247***	0.344
3rd quintile	-0.8116**	0.357	-0.568	0.399	-2.097***	0.605	-2.147***	0.565	-1.852***	0.525	-2.080***	0.452
4th quintile	-0.478	0.481	-0.752	0.550	-0.893*	0.467	-1.030**	0.510	-0.977***	0.325	-1.211***	0.387
Most deprived	-0.397	0.391	-0.542	0.407	-0.796**	0.400	-1.058**	0.439	-0.961**	0.385	-1.274***	0.391
Overall	-1.784**	0.764	-1.371**	0.570	-1.257***	0.421	-1.373***	0.427	-1.064***	0.300	-1.346***	0.297
Flat slope test /1	-6.357	4.110	-3.700	2.708	-0.825	0.527	-0.548	0.479	0.419	0.544	0.326	0.512
Middle slope/2	1.215	0.985	1.004	0.780	-1.047**	0.413	-0.966**	0.395	-0.987**	0.402	-0.919**	0.384
Outcome: Years of life lost as absolute effect of £100 (linear-linear)												
Least deprived	-1412.08	1061.03	-1177.32	806.19	-291.21***	108.33	-318.69***	112.12	-127.34*	70.41	-213.39***	66.20
2nd quintile	-528.26	386.02	-254.96	300.91	-335.45***	111.56	-367.97***	120.25	-217.38***	61.16	-272.84***	78.60
3rd quintile	-212.90**	99.92	-155.02	112.52	-528.13***	147.16	-555.91***	145.69	-469.67***	124.39	-515.97***	108.09
4th quintile	-189.84	147.05	-284.31	173.17	-268.97**	118.62	-317.54**	133.67	-305.24***	90.26	-362.19***	98.72
Most deprived	-123.16	122.79	-184.24	137.33	-168.87	129.97	-247.48*	146.32	-225.53*	129.11	-302.42**	130.37
Overall	-493.25**	216.56	-411.17**	178.71	-318.46***	105.34	-361.46***	115.93	-269.02***	72.63	-333.35***	74.94
Flat slope test /1	-1627.33	1133.95	-963.73	802.03	-188.81	120.83	-121.63	117.40	186.05	154.94	178.38	150.22
Middle slope/2	350.43	271.72	320.19	231.22	-262.01***	94.80	-242.99***	90.51	-250.80***	93.97	-228.26***	86.91
Observations	195		195		32,784		32,784		32,784		32,784	

Notes: Same as appendix Table A4. Estimated coefficients are marginal effects by deprivation group estimated by two-stage least squares with distance from target index (DFT) as the instrumental variable and expenditure interacted with deprivation quintile estimated with five first stages corresponding to each interaction of IV with deprivation quintile.

Appendix Table A6: Alternative IV sets

	No IV (Naive regression)		DFT only (Base case)		DFT + Age-Cost + MFF (IV set in earlier studies)		DFT with Age-Cost + MFF as additional controls	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Outcome: Adjusted mortality elasticities (log-log)								
Least deprived	-0.151	0.130	-0.879***	0.277	0.014	0.084	-0.644**	0.277
2nd quintile	-0.321**	0.151	-1.041***	0.293	-0.193	0.118	-1.100***	0.423
3rd quintile	-0.287**	0.136	-1.010***	0.283	-0.148	0.099	-1.270***	0.341
4th quintile	-0.208	0.138	-0.935***	0.284	-0.073	0.096	-0.847***	0.225
Most deprived	-0.004	0.130	-0.758***	0.290	0.046	0.089	-0.761***	0.275
Overall	-0.194	0.124	-0.925***	0.279	-0.071	0.079	-0.924***	0.264
Outcome: Years of life lost elasticities (log-log)								
Least deprived	-0.537***	0.167	-1.282***	0.319	0.044	0.134	-0.913**	0.362
2nd quintile	-0.529***	0.179	-1.270***	0.310	0.021	0.154	-1.247***	0.344
3rd quintile	-0.605***	0.176	-1.347***	0.314	-0.020	0.148	-2.080***	0.452
4th quintile	-0.857***	0.167	-1.602***	0.311	-0.262*	0.140	-1.211***	0.387
Most deprived	-0.469***	0.179	-1.240***	0.308	0.021	0.149	-1.274***	0.391
Overall	-0.600***	0.137	-1.348***	0.293	-0.039	0.098	-1.346***	0.297

Notes: (same as appendix table A4)

Note: *** p<0.01, ** p<0.05, * p<0.1 No IV yields no overall effect for mortality and YLL. Using the full set of three IVs, as in earlier studies, yields a similar result to No IV. Using the additional two IVs as additional control variables yields similar results to the base case specification.

Appendix Table A7: Sensitivity to inclusion or exclusion of control variables

	With all controls (Base case)		Age-cost index + MFF only		6 IMD domains only		No controls	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Outcome: Adjusted mortality rate as elasticities (log-log)								
Least deprived	-0.879***	0.277	-0.703**	0.285	-0.701**	0.305	-0.626*	0.355
2nd quintile	-1.041***	0.293	-0.819***	0.312	-0.899***	0.323	-0.763*	0.392
3rd quintile	-1.010***	0.283	-0.790***	0.295	-0.868***	0.305	-0.720**	0.365
4th quintile	-0.935***	0.284	-0.633***	0.292	-0.790***	0.305	-0.525	0.360
Most deprived	-0.758***	0.290	-0.226	0.295	-0.673**	0.305	-0.192	0.352
Overall	-0.925***	0.279	-0.634**	0.289	-0.786***	0.302	-0.565	0.359
Outcome: Adjusted mortality as absolute effect of £100 (linear-linear)								
Least deprived	-53.088***	16.672	-40.855**	17.412	-49.101***	18.440	-43.732**	20.966
2nd quintile	-54.606***	17.076	-41.460**	18.473	-54.251***	19.208	-46.654**	22.773
3rd quintile	-52.250***	17.330	-39.945**	18.175	-52.436***	18.799	-45.082**	21.731
4th quintile	-45.412**	17.639	-29.609	18.435	-45.664**	19.157	-32.406	21.948
Most deprived	-20.463	18.694	9.610	19.265	-25.977	19.522	1.907	21.797
Overall	-45.154***	16.913	-28.436	17.742	-45.478**	18.474	-33.179	21.285
Outcome: Life years lost as elasticities (log-log)								
Least deprived	-1.282***	0.319	-1.215***	0.282	-0.986***	0.353	-1.011**	0.453
2nd quintile	-1.270***	0.310	-1.114***	0.267	-1.007***	0.309	-0.920**	0.420
3rd quintile	-1.347***	0.314	-1.150***	0.280	-1.072***	0.330	-0.887**	0.442
4th quintile	-1.602***	0.311	-1.202***	0.267	-1.319***	0.324	-0.868**	0.437
Most deprived	-1.240***	0.308	-0.290	0.258	-1.029***	0.329	-0.086	0.422
Overall	-1.348***	0.293	-0.994***	0.248	-1.083***	0.310	-0.754*	0.419
Outcome: Life years lost as absolute effect of £100 (linear-linear)								
Least deprived	-333.83***	75.46	-313.40***	67.94	-267.15***	80.79	-275.59**	113.79
2nd quintile	-323.15***	73.31	-280.46***	64.13	-265.78***	72.11	-248.69**	108.77
3rd quintile	-354.67***	76.64	-289.95***	69.48	-295.55***	76.99	-242.84**	112.35
4th quintile	-398.31***	77.95	-259.51***	70.57	-337.89***	77.99	-194.55*	114.20
Most deprived	-220.82***	79.50	124.31*	67.82	-178.46**	83.33	149.38	109.45
Overall	-326.12***	70.92	-203.67***	60.72	-268.94***	72.51	-162.33	107.01

Notes: (same as appendix table A4)

Appendix Table A8: With and without London (log-log, small area, DFT)

	(Base case)		(no London)		(London)	
	Estimate	SE	Estimate	SE	Estimate	SE
Outcome: Adjusted mortality rate as elasticities (log-log)						
Least deprived	-0.879***	0.277	-0.814***	0.270	-0.942**	0.387
2nd quintile	-1.041***	0.293	-0.980***	0.277	-1.108***	0.404
3rd quintile	-1.010***	0.283	-0.951***	0.269	-1.079***	0.386
4th quintile	-0.935***	0.284	-0.877***	0.276	-1.005***	0.377
Most deprived	-0.758***	0.290	-0.710**	0.282	-0.838**	0.391
Overall	-0.925***	0.279	-0.865***	0.268	-1.005***	0.383
Outcome: Life years lost as elasticities (log-log)						
Least deprived	-1.282***	0.319	-1.133***	0.325	-0.794**	0.359
2nd quintile	-1.270***	0.310	-1.165***	0.313	-0.826**	0.338
3rd quintile	-1.347***	0.314	-1.280***	0.323	-0.941***	0.333
4th quintile	-1.602***	0.311	-1.563***	0.309	-1.224***	0.324
Most deprived	-1.240***	0.308	-1.184***	0.314	-0.845**	0.335
Overall	-1.348***	0.293	-1.257***	0.297	-0.971***	0.318

*Notes: (same as appendix Table A4, in the main text). *** p<0.01, ** p<0.05, * p<0.1 To the specification stated in equation 3 we add an additional first-stage where the term of London dummy interacted with health expenditure is instrumented with the interaction of the instrument, distance from target, with the London dummy. London includes 4,636 LSOA, which is 14% of total LSOA, with a population of 8,512,291 (15% of England).*

Appendix Table A9: Alternative functional forms (small area, DFT)

		Elasticity (Log-log) (Base case)		Absolute effect of £100 (Linear-Linear)		Percentage effect of £100 (Log-Linear)		Absolute effect of a 1% increase in expenditure (Linear-Log)	
	Baseline mean	Estimated effect	SE	Estimated effect	SE	Estimated effect	SE	Estimated effect	SE
	Outcome: Directly age-sex adjusted mortality rate per 100,000 general population								
Least deprived	777	-0.879***	0.277	-53.088***	16.672	-0.068***	0.021	-6.76***	2.16
2nd quintile	877	-1.041***	0.293	-54.606***	17.076	-0.080***	0.023	-7.01***	2.21
3rd quintile	962	-1.010***	0.283	-52.250***	17.330	-0.078***	0.022	-6.70***	2.24
4th quintile	1125	-0.935***	0.284	-45.412**	17.639	-0.072***	0.022	-5.85**	2.28
Most deprived	1379	-0.758***	0.290	-20.463	18.694	-0.059***	0.022	-2.42	2.43
Overall	1024	-0.925***	0.279	-45.154***	16.913	-0.071***	0.021	-5.75***	2.19
	Outcome: Life years lost under age 75 per 100,000 general population								
Least deprived	2721	-1.282***	0.319	-333.83***	75.463	-0.099***	0.025	-42.47***	9.66
2nd quintile	3193	-1.270***	0.310	-323.15***	73.308	-0.098***	0.024	-41.79***	9.28
3rd quintile	3761	-1.347***	0.314	-354.67***	76.643	-0.104***	0.024	-45.61***	9.80
4th quintile	4527	-1.602***	0.311	-398.31***	77.949	-0.123***	0.024	-51.72***	9.96
Most deprived	6211	-1.240***	0.308	-220.82***	79.497	-0.095***	0.024	-28.69***	10.29
Overall	4084	-1.348***	0.293	-326.12***	70.918	-0.104***	0.023	-42.05***	9.05

*Note: *** p<0.01, ** p<0.05, * p<0.1 Expenditure per capita in different CCGs ranges from £1,039 to £1,670. So an increase of £100 per capita is just under a 10% increase, though this will vary by CCG and small area deprivation group. The linear-linear model regresses the outcome (adjusted mortality or YLL) against expenditure in pounds divided by 100. The log-linear model regresses the log of the outcome (mortality or YLL) against expenditure in pounds divided by 100, and then multiplies the coefficient by 100 to convert to a percentage effect. Because baseline mean mortality is higher in more deprived quintile groups of small areas, the same percentage effect of £100 implies a larger absolute effect of £100. Because baseline mean expenditure is also higher – though to a lesser extent than baseline mortality – the same elasticity also implies a larger absolute effect of £100 in more deprived quintile groups of small areas, though to a lesser extent.*

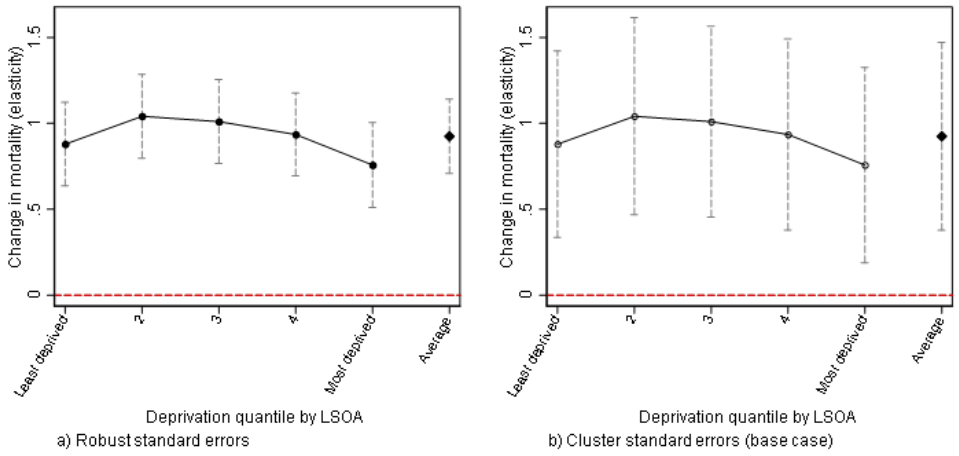
Appendix Table A10: Estimated coefficients using our base case specification (DFT) and MFF adjusted health expenditure allocation

	Elasticity (Log-log) (Base case)		Absolute effect of £100 (Linear-Linear)	
	Estimate	SE	Estimate	SE
Outcome: Directly age-sex adjusted mortality rate per 100,000 general population				
Least deprived	-0.907***	0.275	-50.93***	16.84
2nd quintile	-0.982***	0.278	-50.28***	17.17
3rd quintile	-0.923***	0.275	-47.11***	17.28
4th quintile	-0.970***	0.287	-45.51**	17.63
Most deprived	-0.800***	0.289	-21.99	18.06
Overall	-0.916***	0.277	-43.16**	17.08
Outcome: Life years lost under age 75 per 100,000 general population				
Least deprived	-1.220***	0.299	-325.19***	68.86
2nd quintile	-1.328***	0.298	-328.47***	68.49
3rd quintile	-1.343***	0.294	-333.18***	68.38
4th quintile	-1.515***	0.300	-356.26***	70.28
Most deprived	-1.261***	0.295	-220.85***	70.89
Overall	-1.333***	0.286	-312.76***	66.37

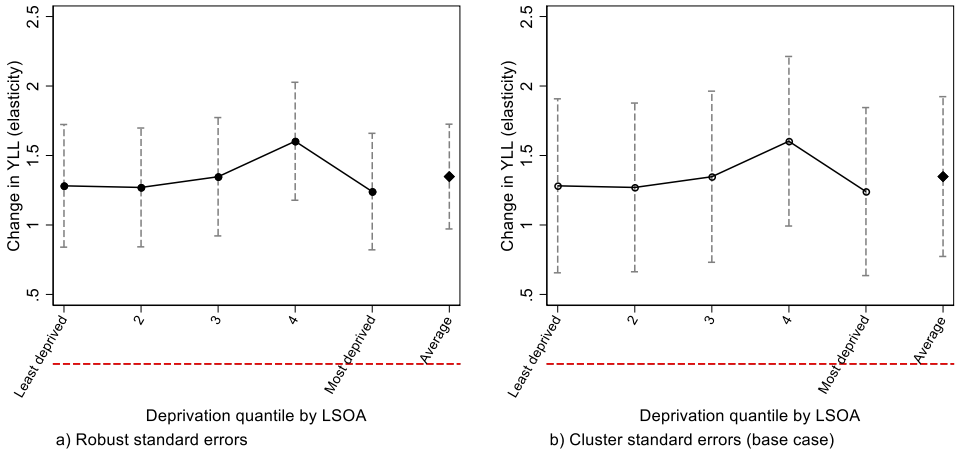
*Notes: (same as appendix table A4, in the main text), instead of health expenditure we use market forces factor adjusted health expenditure. *** p<0.01, ** p<0.05, * p<0.1*

Appendix Figure A1: Base case results with robust vs clustered standard errors

(a) Adjusted mortality



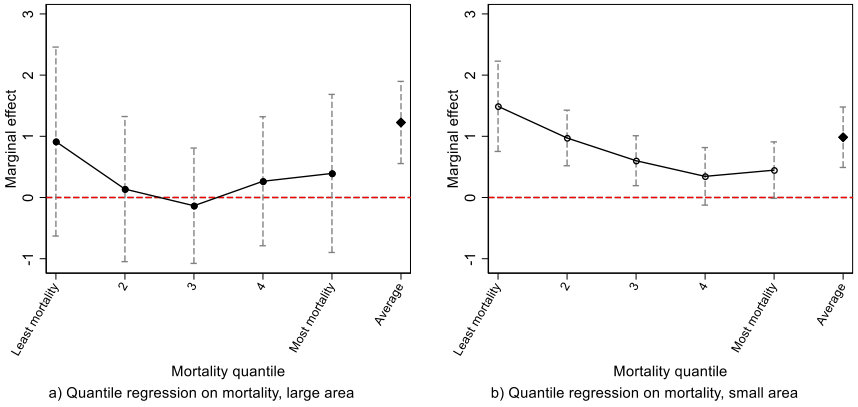
(b) Years of life lost



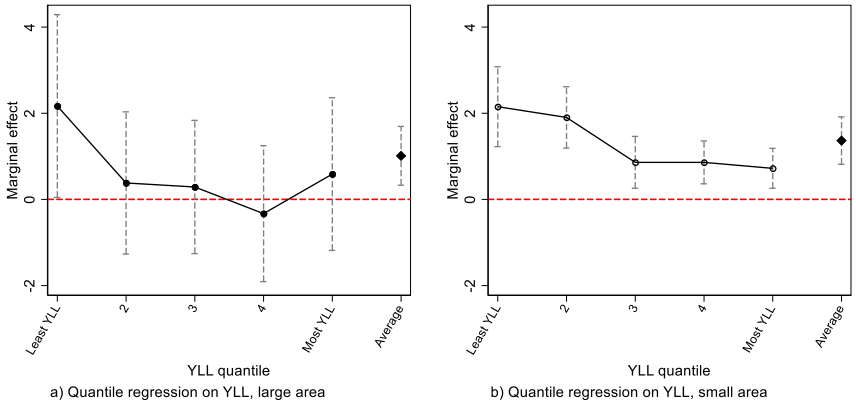
Note: The alternative of using robust standard errors, rather than our approach of clustering small areas within CCGs, yields smaller confidence intervals. The standard large area approach obviously cannot cluster by CCG because CCG is the unit of observation.

Appendix Figure A2: Unconditional quantile regression version of our base case (DFT, log-log, small area stratification)

(a) Adjusted mortality

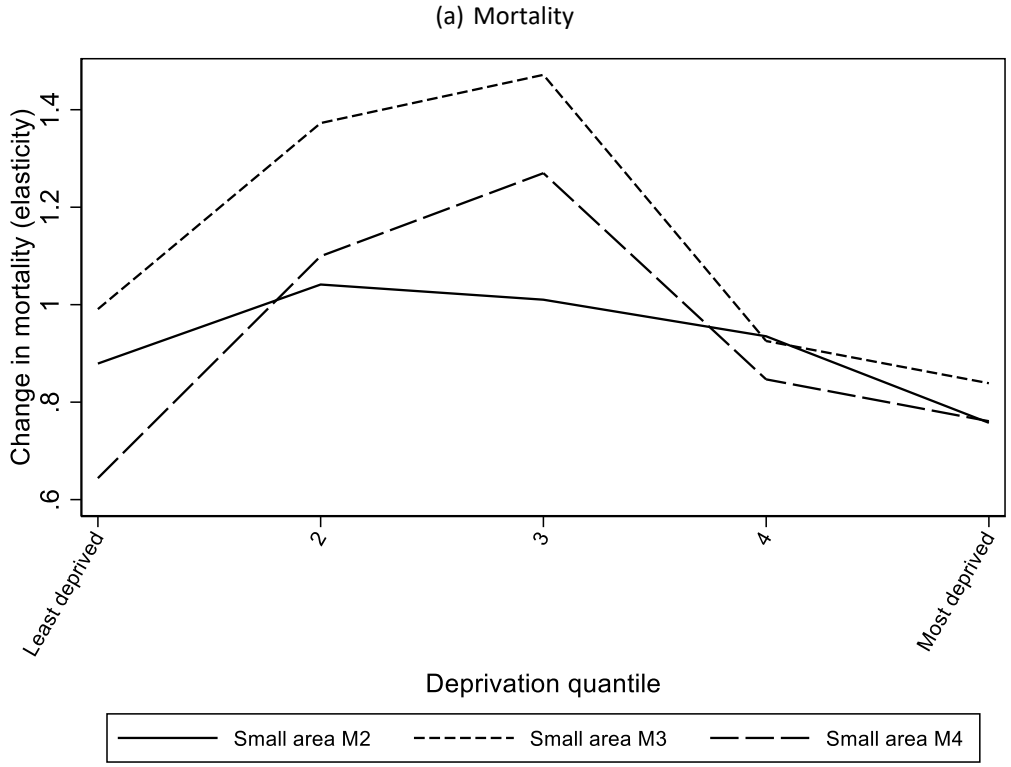


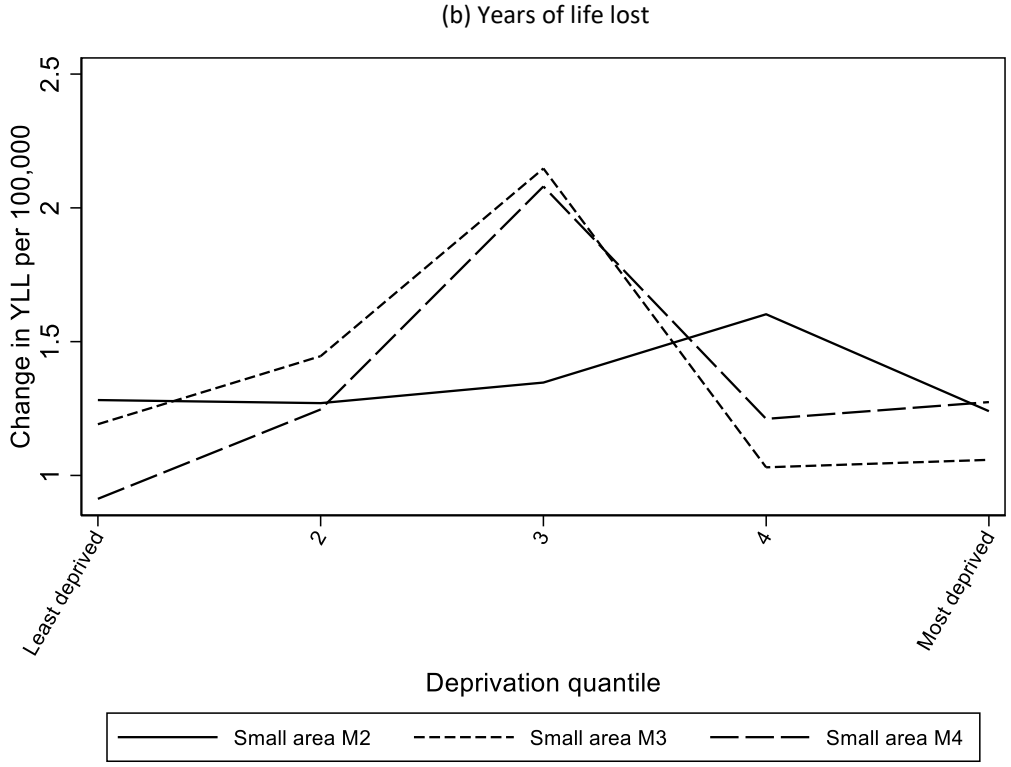
(b) Years of life lost



Note: Unconditional quantile regression by large area stratification (GCG) and by small area stratification (LSOA), vertical lines show 95% confidence intervals.

Appendix Figure A3: Graphical comparison of elasticities from main results and sensitivity analysis using five first stages





Notes: The figures display the elasticities estimated in Table 3 and Appendix Table A5. Small Area M2 corresponds to Column 3 of Table 3, Small Area M3 to Column 4 of Appendix Table A5, and Small Area M4 to Column 6 of Appendix Table A5. Confidence intervals are not shown.

Part of