Vertical and horizontal inequity in area level allocations of cancer spending in England

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Abstract

We aim to analyse vertical inequity (VI) and horizontal inequity (HI) in area level allocations of expenditure for cancer across Primary Care Trusts (PCTs) in England. We investigate VI and HI with respect to deprivation and needs. We use information on PCT spending on cancer from 2004/05 to 2008/09 extracted from Programme Budgeting data. A dataset of PCT variables is assembled from publicly available sources on cancer prevalence and mortality, demographic profiles, deprivation, and health care supply. In addition, we create a cancer-related severity index using information from a household survey. Various econometric specifications are investigated to regress cancer expenditure against the covariates accounting for the longitudinal nature of the data. We measure inequity using the concentration index approach, and identify contributions to inequity using decomposition techniques. To measure inequity we use both deprivation and needs as ranking variables. We show that unadjusted cancer expenditure is concentrated in poorer and sicker areas. Our findings indicate no evidence of statistically significant HI with respect to deprivation and needs. The VI estimates are positive in both cases, indicating pro-rich and pro-healthy vertical inequity, but only the latter is found to be weakly significant. Total inequity estimates (HI + VI) indicate that while spending appears to be equally distributed across affluent and deprived areas; there is some evidence of inequity favouring healthier regions. We show that an equitable allocation with respect to the deprivation distribution does not necessarily mean that health care resources are being distributed appropriately according to need.

1. Introduction

The major aim of promoting equity in the English NHS becomes obvious in many government documents and academic studies. Since mid-1970s, attention to inequalities in expenditure between administrative areas has become even more explicit, with a resource allocation formula designed to eliminate such inequalities by distributing NHS resources on the basis of explicit equity objectives.

Such objectives often subscribe to egalitarian goals, which suggest that health care should be distributed according to 'need' (Wagstaff & van Doorslaer, 2000). This can include horizontal and/or vertical equity principles. The horizontal equity principle requires that individuals with the same needs receive the same treatment. The vertical equity principle requires that those with different needs receive appropriately different care. Taken together, these principles suggest not only that patients with the same health status should receive the same treatment irrespective of, for instance, their social class, but also that those suffering from worse ill health should be properly prioritised in receiving health care.

However, there continues to be widespread concern about the variation in the magnitude of spending in health care across Primary Care Trusts (PCTs) in England, particularly in mental health, cancer and circulatory diseases (Appleby & Gregory, 2008). Measuring inequities in area level allocations is not straightforward. A common issue when analysing inequities in area level health care delivery is that measures of needs are often very crude. We focus in this analysis on area level spending on a specific disease programme - cancer. The focus on

cancer spending allows us to use disease-specific health measures that are more likely to capture need for disease-specific health care resources (van Doorslaer *et al.*, 2006). The cost of this approach is highlighted by Propper et al., 2005 who argue that *"the results will apply only to a single particular condition, which means the condition must be one that a large number of individuals suffer from and on which considerable public and private resources are spent"*. Cancer is the leading cause of death worldwide (World Health Organization, 2011), and despite improvements in survival and mortality in recent decades, cancer outcomes in England remain poor when compared with the best outcomes in Europe (Department of Health, 2011). According to the Programme Budgeting Data (PBD) analysis of expenditure by disease programme[1], the NHS spent £5.86 billion on cancer in 2009/10.

With respect to previous evidence, most analyses of inequity in health care allocations at the area level in the literature have focussed on variations in utilisation rates of elective surgery across socioeconomic groups. Goddard & Smith, 2001 and Dixon *et al.*, 2007 identified several studies that support the idea that cardiac surgical intervention rates are larger in more affluent areas. In the studies where higher rates were found in more deprived areas, the gradients were not sufficient to match the socioeconomic differential in mortality. Operation rates for other conditions amenable to surgery, such as arthritis of the hip, have also been found to be lower in more deprived areas (Chaturvedi & Ben-Shlomo, 1995). Cookson *et al.*, 2010 estimated small area associations between two procedures (hip replacement and coronary revascularisation) with area deprivation after controlling for needs and supply indicators. They found a small area deprivation gradient with utilisation rates falling in the most deprived areas for both surgical procedures.

In the case of cancer service delivery, Goddard's & Smith's review found that screening uptakes rates were lower in areas with higher levels of deprivation, and these findings were supported by a later review from Dixon *et al*., 2007. Cancer patients living in more deprived areas have also been found to be more likely to be diagnosed after an emergency admission, which is a maker of poor outcome (Pollock *et al.*, 1998). In addition, lower chemotherapy rates for colorectal cancer patients have been found for individuals living in more deprived regions (Mclead, 1994). Campbell *et al.*, 2002 found that socio-economic and rurality status of the area of residence have a minor impact on modalities of treatment for colorectal and lung cancer, but do not lead to delays between referral and treatment in Scotland. There is some evidence also from Scotland that suggest no differences in access or treatment for breast cancer between women living in more affluent and deprived areas (Macleod *et al.*, 2000). Therefore, there is evidence of poorer treatment in more deprived areas, but also evidence of equal treatment (Dixon *et al.*, 2007) in cancer care services allocation. Note however, that all the evidence summarised above consider only variations in utilisation rates, but it does not account for differential costs for similar episodes of care that would also influence variations in spending. For instance, previous evidence on length of stay after hip replacement have found that individual from the most deprived areas tend to stay longer in hospital and thus cost more to treat (Cookson & Laudicella, 2011).

With respect to inequities in cancer spending, considerable variations across Primary Care Trusts (PCTs) have been found after adjusting for local cost and need variation factors. Expenditure on cancer was found to vary around 2.2-fold between Knowsley PCT spending £118 per head, compared with £53 by Bedfordshire PCT (Appleby & Gregory, 2008). Variations in spending on disease-specific programme are not unimportant, as they have been

[1] http://www.dh.gov.uk/en/Managingyourorganisation/Financeandplanning/Programmebudgeting/

found to have an impact on health outcomes. The effect of health care spending on health outcomes such as disease-specific mortality and years of life lost (YLL) have been recently estimated using the PBD (Martin et al., 2008; Martin et al., 2011). The authors found that after accounting for endogeneity, expenditure on cancer services significantly reduces mortality from cancer. Similar results were found for other disease programmes.

In our analysis we aim to measure inequity in the allocation of cancer expenditure across PCTs in England using five years of data from 2004/05 to 2008/09. We aim to answer the questions of whether allocations of cancer expenditure are appropriately distributed according to needs, and if not, to measure the extent to which areas with larger deprivation and/or areas with larger medical needs are being disfavoured in the provision of health care. Therefore, in addition to the standard focus on socioeconomic-related inequity in the provision of health care, we propose to investigate inequities with respect to a measure of need. This analysis is also novel in that we measure both horizontal and vertical aspects of inequity in health care spending. The vast majority of empirical research on equity in health care delivery has focused solely on the horizontal equity principle. We exploit the longitudinal nature of our data by testing different econometrics specifications as well as by incorporating the panel-based methods in our measures of inequity.

The paper is structured as follows, the next section summarises the methodology for the measurement and explanation of inequity indices using longitudinal data. The empirical methods and econometrics models are explained next. The data section summarises the variables used in the regression models. Empirical results from the econometric models, inequity indices and decomposition analyses are then presented. The final section concludes and provides a discussion of the main results.

2. Measurement and explanation of inequity using longitudinal data

2.1.Measurement of inequity using longitudinal data

We use the concentration index (CI) approach to quantify inequity in health care allocation (Wagstaff *et al.*, 1991). CIs are bivariate measures of relative inequality, measuring inequality in one variable (in our case health care spending) related to the ranking of another variable (in most cases an indicator of socioeconomic status (SES)). In our analyses we quantify inequity using both a measure of socioeconomic deprivation and a measure of health care needs as ranking variables in order to measure SES-related and need-related inequity in cancer spending, respectively. Note that the SES-related analysis examines whether health care spending is disproportionally concentrated on more affluent/deprived areas. The need-related dimension captures whether inequities in health care allocation are disfavouring areas with relatively larger/lower needs for resources.

Most analyses of equity in health and health care have focused on measures of inequalities designed for use with cross sectional data. However, Jones & López Nicolás, 2004 emphasised the desirability of the longitudinal perspective in the measurement of income-related inequalities in health. They proposed a measure of health inequality inspired in the literature of income mobility (Shorrocks, 1978). This approach considers inequality in health averaged across a sequence of periods of time across the distribution of income averaged across this sequence of periods of time. They found that measuring longer term health inequality by simply taking a weighted average of the inequality estimated in each year tends

to underestimate long-run inequality as measured in their proposed way. Bago d'Uva *et al*., 2009 applied a similar methodology to the context of horizontal inequity in health care. They also found that panel-based method lead to significantly higher estimates of horizontal inequity.

Following Jones & López-Nicolás, 2004, we take the longitudinal approach for the measurement of inequity in health care spending. Long-run (LR) inequality in health care spending is measured as the concentration index, CI_T, for the average actual expenditure across periods, using as ranking variable the average need or deprivation measure across periods. Only when variations in the ranking variable across time are not associated with systematic differences on the spending distribution, this measure of inequality equals the weighted average of the short-run (ASR) concentration indices defined as,

$$CI^{ASR} = \sum_t w_t CI_t \text{ , where } w_t = \frac{\overline{q}_t}{T\,\overline{\overline{q}}_T} \tag{1}$$

where T is the number of periods, $\overline{q}_t$ is the average spending in period t, and $\overline{\overline{q}}_T$ is the average spending across the T periods. The CI lies between –1 and +1, with positive values indicating a pro-rich (pro-healthy) concentration of health care resources across the socioeconomic (need) distribution.

Finding that the CI_T of actual spending is not zero only tells the analyst something about *inequality*, i.e. different areas spend different amount of resources, but it tells very little in terms of *inequity* as we are not taking into account differences in needs in the populations. We apply the methodology developed by Sutton, 2002 to measure separately horizontal and vertical aspects of inequity. Long-run *horizontal* inequity can be measured as the difference between the CI_T of actual utilisation and the CI of the average need-predicted health care spending across periods,

$$HI_T = CI_T - CI(\hat{q}_i) \tag{2}$$

Need-predicted health care spending is created using a regression model of health care expenditure against a number of need and non-need variables, and neutralising the effect of the non-need variables by setting the variables equal to their mean values in the prediction,

$$\hat{q}_{it} = \alpha + \sum_k \hat{\beta}_k N_{itk} + \sum_j \hat{\delta}_j \overline{Y}_j + \varepsilon_{it} \tag{3}$$

where *i* indexes individuals (PCTs in our analysis) and *t* indexes time periods. In order to quantify *vertical* equity, Sutton, 2002 proposed comparing the need-predicted allocation with the allocation resulting from a target distribution of health care. The target allocation of health care is derived from the predicted values of the health care expenditure equation where the need variables have the optimal (or vertically equitable) effect on spending. We thus measure long-run vertical inequity as the difference between the CI of the average need predicted allocation and the CI of the average target allocation across periods of time,

$$VI_T = CI(\hat{q}_i) - CI(q_i^*) \tag{4}$$

The target allocation is given by Equation (5), where the need variables have the optimal effect on spending (details for the estimation of the optimal effect of the need variables are provided below) and the effect of the non-need variables are again neutralised,

$$q_{it}^{*} = \alpha + \sum_{k} \beta_{k}^{*} N_{itk} + \sum_{j} \hat{\delta}_{j} \overline{Y}_{ij} + \varepsilon_{it} \tag{5}$$

Finally, long-run total inequity can be measured as the sum of horizontal and vertical inequity indices, or alternatively as the difference between the CI of the average actual spending and the CI of the average target expenditure allocation over time,

$$TI_{T} = CI_{T} - CI\left(q_{i}^{*}\right) \tag{6}$$

2.2. Explanation of inequity using longitudinal data

One of the useful features of CIs is that they can be decomposed using regression analysis techniques. This means that it is possible to measure the contribution of different factors (covariates in the regression model) to inequities in the delivery of health care (Wagstaff *et al.*, 2003). In the case of using longitudinal data the decomposition of inequality in health care expenditure is defined as,

$$CI_{T} = \sum_{k} \left(\frac{\beta_{k} \overline{\overline{N}}_{k}}{\overline{\overline{q}}_{T}}\right) CI_{T}^{k} + \sum_{j} \left(\frac{\delta_{j} \overline{\overline{Y}}_{j}}{\overline{\overline{q}}_{T}}\right) CI_{T}^{j} + \frac{GC_{\varepsilon}}{\overline{\overline{q}}_{T}} \tag{7}$$

where $\overline{\overline{N}}$ and $\overline{\overline{Y}}$ are the mean values of the need and non-need variables; CI_{T}^{k} and CI_{T}^{j} are the CI of the average need and non-need variables with respect to the average of the ranking variable across time; and GC_{ε} is the generalized concentration index (CI times the mean) for the error term.

The individual contribution of each of the non-need variables to inequality in health care spending provides the decomposition of horizontal inequity. The decomposition of the vertical inequity estimate is derived by looking at the differences for each of the need indicators included in the regression between the contribution of the need indicator based on its estimated and its target effect on spending,

$$VI_{T} = \sum_{k} \left(\hat{\beta}_{k} - \beta_{k}^{*}\right) \frac{\overline{\overline{N}}_{k}}{\overline{\overline{q}}_{T}} CI_{T}^{k} \tag{8}$$

3. Empirical models and estimation methods

We adopt a similar estimation strategy as that proposed by Cornwell & Ruppert, 1988 and followed by Contoyannis and Rice, 2001. Our model of health care spending across five years of data is regressed against a number of time variant and time invariant covariates among the need and non-need indicators. Our specification of the expenditure equation in the context of longitudinal data is thus,

$$q_{it} = \alpha + \sum_k \beta_k N_{itk} + \sum_h \gamma_h N'_{ih} + \sum_j \delta_j Y_{itj} + \sum_l \varphi Y'_{il} + \alpha_i + \varepsilon_{it} \quad (9)$$

where N'_{ih} and Y'_{il} are time-invariant need and non-need variables, respectively; α_i is an area specific and time invariant error component (known as the unobserved individual effect); and ε_{it} is a classical idiosyncratic disturbance assumed to be uncorrelated with both the individual covariates and the α_i. Ordinary Least Square (OLS) and random effects (RE) models assume the covariates to be uncorrelated with the unobserved individual effect. However, the unobserved individual effect α_i might be correlated with (be endogenous to) some covariates in the model, and this can be controlled for in the specification of the econometric model using specific panel data techniques. The traditional solution in the presence of correlation of α_i with the covariates in the model is to use fixed effects (FE) (also known as 'within' estimators) which transform the data into deviation from the individual means. The major limitations of this method are that time invariant variables cannot be included in the analysis and that it is not fully efficient as it ignores variation across observations. Hausman and Taylor (HT), 1981 and Amemiya and MaCurdy (AM), 1986 proposed instrumental variable (IV) specifications using internal instruments that control for the correlation of the unobserved individual effect and the covariates suspected to be endogenous[2]. These estimators have the advantage of allowing time invariant variables to be included. In addition, they are generally more efficient than fixed effects estimators as they exploit the assumptions about which explanatory variables are exogenous.

We experiment with simple OLS regressions that allow for clustering at the PCT level and RE specifications which assume exogeneity. Validity of the OLS model can be tested by running a RE model and performing the Breusch-Pagan test. Hausman test are carried out to test for the correct specification (exogeneity) of the random effects estimates, i.e. under the null of exogeneity the fixed effects estimates should be close to the random effects estimates for the time varying variables. Time invariant variables cannot be compared as the fixed effects specification does not allow its inclusion. Therefore, even in the case that the Hausman test does not reject exogeneity of the time variant covariates, the use of the IV estimators may be preferred as they allow for the inclusion and potential endogeneity of time invariant covariates (Contoyannis & Rice, 2001). For the IV estimators it is necessarily to consider a priori partitioning of the variables into exogenous and endogenous components. The HT estimator then uses the mean values of the assumed time-varying exogeneous variables to (over) identify the parameters of the time invariant endogenous variables. The time varying endogeneous variables are instrumented using the deviation from the means of the time varying exogenous regressors. The AM estimator uses the level of each time varying exogenous variable at each time period *t* to instrument the time invariant endogenous variables. In both cases the models would be inconsistent if some of the variables assumed to be exogenous are correlated with α_i. We can test for this by running a Hausman test that compares the fixed effect estimates with both the HT and AM estimates. If consistent, the AM estimates provide potential efficiency gains over the HT estimators.

Most of the previous empirical literature have derived standard errors (SE) around the HI estimates by computing the need-standardised allocation of health care, defined as the

[2] There is an additional variant of the IV estimators proposed by Breusch, Mizon and Schmidt, 1989 which is not considered in this analysis.

difference between the actual allocation and the need-predicted allocation plus the mean of the actual allocation. The CI of the need-standardised variable provides the measure of HI, and standard errors around this point estimate have been used to assess the statistical significance of the horizontal inequity estimate. The methods traditionally employed allow correcting SEs for cluster design and adjust for sample weights, or autocorrelation, but they ignore the extra uncertainty introduced by the fact that the need-predicted variable is derived from the predicted values of a regression model. The implications for the vertical equity estimate are even more pronounce as this estimate is derived from the difference between two predicted variables, i.e. the need-predicted and the target allocation of health care. Therefore, we use bootstrapping techniques using 500 replications to compute SEs around the estimates of HI, VI, and TI. Following van Doorslaer *et al.*, 2004, bootstrapping techniques are also used to estimate the SEs around the contribution of the individual covariates to our measures of inequity.

4. Data

4.1. Programme Budgeting Data (PBD) – Expenditure on cancer programme

Programme budgeting is the analysis of expenditure in health care programmes. Data have been collected annually for 23 main programmes of care based on the World Health Organisations International Classification of Diseases (ICD10) – including cancer programme, since 2003/04. The data is available by Primary Care Trusts (PCT). Thus we use PCTs as unit of analysis in our models of which there were 152 at the time of the analysis with an average population of 400,000. PBD includes most items of publicly funded expenditure, including inpatient, outpatient and community care, and pharmaceutical prescriptions. The programme-specific figures do not include GP cost, social care cost, and prevention costs which are reported separately. The PCT level expenditure figures are for expenditure on own population which is net expenditure, adjusted to add back expenditure funded from sources outside of the NHS and to deduct expenditure on other PCTs populations through lead commissioning arrangements. We use data for PCTs on "Expenditure on own population (£000s)" for the financial years (FY) 2004/05 until 2008/09. We regress total spending on cancer against a number of need and non-need indicators. The reason for looking at total expenditure rather than expenditure per head or per case is that if expenditure is not proportional to cases (some cases cost more than others), a model that uses expenditure per case as the dependent variable would be misspecified (Gravelle & Hole, 2008).

Raw figures of PCT expenditure do not adjust for unavoidable geographical variation in costs. The Hospital and Community Health Services Market Forces Factor (HCHS MFF) is used to achieve this cost adjustment.

Appendix 1 summarises the data used as covariates and target indicators in the models of cancer expenditure across Primary Care Trusts. In the Appendix we include the name, description, summary statistics, availability by year, sources of the data and original geography availability of the data.

4.2.Need indicators

The variables considered to be need indicators are: the total counts of cancer cases (excluding non-melanoma skin cancer); standardised mortality ratio (SMR) from all cancers; total population size; age and gender area profile and mean EQ-5D of individuals suffering from cancer. The latter is created using information from the Health Survey for England (HSE) by

combining data from the years 2004-2006 and 2008 where EQ-5D data were available. The geographical unit available in these survey years in the HSE are the 10 Strategic Health Authorities (SHA). We compute this measure of PCT-specific cancer severity by:

a. Regressing EQ-5D scores among individuals reporting cancer using an OLS model against a number of individual and area level variables at the SHA level. The individual level variables included are: a cubic function of age and its interaction with gender, gender, and the presence and number of other longstanding illnesses. The SHA level variables are included in the model are: percentage of individuals in different age group, percentage of males and percentage of individuals in various ethnic groups. The model also controls for year.
b. Multiplying the estimated effect of the individual level variables by their SHA-specific mean values and adding this to the constant to create a SHA-specific constant term.
c. Adding this to the estimated coefficients of the area level variables multiplied by the PCT level version of these area level indicators. Therefore, individual level variables are used to create a constant SHA-specific value to which we add the effect of the area level variables estimated using information at the SHA level but then used to predict EQ-5D at the PCT level.

4.3. Non-need indicators

Additional data on socioeconomic and supply area characteristics are included in the regression models. The following variables are considered non-need indicators for cancer expenditure: total counts of job seekers' allowance claimants; education scores from the Index of Multiple Deprivation; ethnicity; severity in other disease areas proxied by SMR for coronary heart disease (CHD), chronic obstructive pulmonary disease (COPD) and stroke; number of GPs per 100,000 population; average distant to GP premises; average capacity at acute providers; and average distance to acute providers. The models also include year indicators.

4.4.Target indicators

The underlying assumption behind the horizontal inequity analysis is that the estimated effects of the need indicators on spending recovered from the regression model across the full sample are appropriate. We challenge this assumption and seek to identify subsamples of PCTs that best meet the need of their population by allocation resources appropriately according to needs. We then regress our expenditure equation in this subsample and imposed their coefficient of the need variables to the full population to estimate the target distribution defined in Equation (5). We use a series of indicators that fall into four different categories; i) cancer outcomes, ii) treatment services and prevention, iii) World Class Commissioning (WCC) scores in relevant competencies[3], and iv) PCTs that allocate the largest amount of resources to the neediest areas. In terms of the specific target indicators, the following 14 criteria were used to select PCTs to be included in the target group:

1. PCTs with lowest SMR from all cancers for individuals under 75 year-old in 2008/09.
2. PCTs with best 5-year survival rates for eight types of cancers for individuals diagnosed in 2001-2003 and followed up to 2008.

[3]http://webarchive.nationalarchives.gov.uk/+/www.dh.gov.uk/en/Managingyourorganisation/Commissioning/Worldclasscommissioning/index.htm

3. Compliance with the 62-day treatment standard between urgent referral and first treatment for cancer in 2008/09.
4. PCTs with largest number of referrals per 10,000 population through two-week wait in 2008/09.
5. PCTs with largest proportion of cancer patients diagnosed through two-week wait referrals in 2008/09. This referral route has been related to better outcomes for cancer patients (National Cancer Intelligence Network, 2010)[4].
6. PCTs with largest proportion of cervical cancer screening programme coverage among females aged 25-64 in 2008/09.
7. PCTs with largest proportion of breast cancer screening programme coverage among females aged 53-70 in 2008/09.
8. PCTs with lowest proportion of lung cancer diagnoses after emergency admission in 2005/06 (latest data available).
9. PCTs with lowest proportion of pancreas cancer diagnoses after emergency admission in 2005/06 (latest data available).
10. Meeting WCC Competency 2 "Work collaboratively with community partners to commission services that optimise health gains and reductions in health inequalities" at level 2 or above in 2008/09.
11. Meeting WCC Competency 5 "Manage knowledge and undertake robust and regular needs assessments that establish a full understanding of current and future local health needs and requirements" at level 2 or above in 2008/09.
12. Meeting WCC Competency 6 "Prioritise investment according to local needs, service requirements and the values of the NHS" at level 2 or above in 2008/09.
13. PCTs with the largest coefficient of the number of cancer cases explanatory variable in our preferred regression model. We run the preferred cancer spending model separately in every SHA. This yields 10 sets of regression results. We then select the SHAs with the largest, more positive, coefficients on the variable considered to be the most relevant indicator of need for cancer spending, i.e. the number of cancer cases.
14. PCTs with largest needs index in our models. A potential problem with the above approach to identify 'responsive' SHAs is that in some responsive SHAs the coefficient on one need indicator, such as count of cancer cases, may be higher than in an unresponsive SHA, but on another need indicator, such as the severity index, it may be lower. However, the aggregate effect is that the first SHA is more responsive to local needs than the second. To account for this issue we can compute the combined effect of the coefficients by computing an indicative needs index for an area with a predefined set of characteristics. We follow the same approach than that used in the reviews of the resources allocation formulae (Sutton *et al.*, 2002; Morris *et al.*, 2006). We run the preferred spending model separately in every SHA. We compute an indicative needs index for the average area using each set of coefficients by:
    a. Multiplying the coefficient on every non-need variable (including the regional indicators and supply variables) by its SHA population-weighted mean value and adding this to the constant term in the SHA regression model.
    b. Adding to this the coefficient on every needs indicator multiplied by the national mean value of each needs indicator.
    c. Dividing the resulting variable by its population-weighted mean value to give an indicative additional needs index that is centred on unity. We label this the 'responsiveness score'. This yields 10 responsiveness scores; one based on each

[4] http://www.ncin.org.uk/publications/data_briefings/routes_to_diagnosis.aspx

set of SHA coefficients. We rank SHAs coefficients according to the value of the responsiveness score and we select the most responsive SHAs.

The baseline estimates of vertical inequity are computed using a combination of all the above target indicators defined as the 70% of PCTs meeting the largest number of the 14 individuals targets specified above. We consider the indicator to be met if the PCTs fall into the best 70% performers for those indicators that are specified as a continuous variable, e.g. 70% of PCTs with the largest proportion of breast cancer screening programme coverage.

The rational for selecting a cut-off of 70% rather than, for instance 50% as Sutton *et al*., 2002 and Morris *et al.*, 2006, is that the number of observations in our data are considerably lower, and selecting the 50% would imply running our models on just over 70 PCTs. The 70% cut-off also allows us to have a similar number of observations under every target, and so it is not likely that differences in the results are driven by the different number of observations selected under different targets. For instance, some targets rely on data only available at the SHA level of which there are 10 in England. The closest consistent number involved selecting the best six SHAs in every case which included around the 70% of PCTs. Four indicators are given by whether the PCT meets or not a specific target, i.e. compliance with 62-day treatment (84%), achievement of level 2 or above in WCC Competency 2 (95%), achievement of level 2 or above in WCC Competency 5 (73%) and achievement of level 2 or above in WCC Competency 6 (43%). There is unavoidable variation in the number of observations for these target indicators.

5. Empirical results

5.1. Model results

Table 1 presents the results for the regression models. We compare OLS, simple random effect, fixed effect and random effect instrumental variable estimators suggested by Hausman & Taylor and Amemiya & MaCurdy.

The pooled OLS model with PCT level clustering is rejected. The Hausman test does not reject the RE model; however, this test only compares the coefficient of the time-varying variables, and, further, the differences in the parameter estimates of a series of variables in the RE and FE models appear to justify scepticism in relation to this result. As noted above FE model is limited by the fact that only time varying variables can be included in the analysis. The panel data IV estimators are capable of overcoming the problem of endogeneity and offer efficiency gains over the fixed effects estimators. Further, these estimators have the advantage over the FE and RE estimators of allowing the effect of endogeneous time-invariant variables to be consistently estimated. For the IV estimators it is necessarily to consider a priori partitioning of the variables into exogenous and endogenous components. In our regression model it is likely that we are not capable of controlling fully for variation in needs for cancer expenditure. Therefore, a number of variables included in our model are likely to be correlated with unobserved measures of needs that are also correlated with expenditure on cancer. The following variables are thus considered to be correlated with the unobserved individual effect: number of job seekers' allowance claimants; index of multiple deprivation – education domain; standardised mortality ratio for all cancers; and mean predicted EQ-5D of individuals suffering from cancer.

The effect of the number of cancer cases is significant and positive in every model. Our measures of severity defined by SMR from all cancers and the cancer-specific severity index

become strongly significant and their effects are considerably larger after accounting for endogeneity. The size of the population is significant and positively related to total cancer spending in every model with the exception of the FE estimators which ignore variation across PCTs. Only the oldest age category has a significant and positive effect in every model; the percentage of males leads to higher cancer expenditure levels.

Table 1. Models of expenditure on cancer programme (£0,000) across PCTs

	OLS		RE		FE		HT		AM	
	Coef	**z**	**Coef**	**z**	**Coef**	**z**	**Coef**	**z**	**Coef**	**z**
Cases	1.050	2.94	1.170	4.92	1.441	3.66	1.336	5.57	1.283	5.42
SMRcancer	21.16	0.74	49.12	1.62	65.73	1.95	66.07	2.13	68.88	2.26
EQ5Dcancer	-1862.2	-1.24	-3234.8	-2.37			-4915.7	-2.82	-4480.8	-2.69
Population	0.063	15.24	0.064	18.23	0.083	1.07	0.068	14.85	0.067	15.02
Age09p	-159.6	-0.26	59.26	0.08	1063.1	0.66	282.0	0.28	279.0	0.28
Age1019p	Base category		Base category		Base category		Base category		Base category	
Age2039p	-492.1	-0.96	-506.5	-1.05	669.4	0.55	-515.9	-0.78	-527.1	-0.82
Age4059p	-604.3	-1.23	-110.7	-0.19	2221.9	1.31	206.9	0.25	64.2	0.08
Age6074p	-533.4	-0.63	-1026.1	-1.41	370.6	0.21	-1277.5	-1.38	-1243.6	-1.36
Age75plusp	1626.0	2.40	2526.5	3.44	4085.7	1.96	3246.9	3.56	3141.5	3.46
Malesp	1862.3	1.81	2794.8	2.78	4409.4	2.31	3761.1	3.02	3627.4	2.98
JSA	0.952	3.35	0.748	3.44	-0.109	-0.29	0.163	0.50	0.353	1.21
IMDeduc	52.94	0.80	72.25	1.06	84.87	0.33	114.36	0.86	60.48	0.56
Whitep	Base category		Base category		Base category		Base category		Base category	
Asianp	-176.35	-2.93	-146.37	-1.93	-301.84	-0.24	-97.93	-0.82	-118.98	-1.02
Blackp	-43.39	-0.28	192.87	1.03	1239.66	1.47	543.30	2.06	450.92	1.76
Chinp	304.10	0.38	533.94	0.49	-176.17	-0.05	869.81	0.54	731.38	0.46
Otheretp	538.40	0.97	523.33	0.62	-3154.9	-0.83	158.31	0.13	200.88	0.16
GPs	23.09	0.69	-37.56	-1.02	-171.02	-3.12	-97.29	-2.26	-98.12	-2.29
GPdistant	130.43	0.40	-72.55	-0.17	-284.43	-0.56	-240.70	-0.55	-231.36	-0.53
Inpcap	0.009	0.64	0.004	0.19			-0.006	-0.19	-0.01	-0.15
Inpdistant	-0.877	-0.01	29.55	0.42			40.96	0.37	35.54	0.32
Northwest	Base category		Base category				Base category		Base category	
Northeast	-1339.1	-1.51	-1076.1	-0.77			-441.7	-0.19	-347.5	-0.16
Yorkshire	-366.2	-0.31	-321.9	-0.24			-101.4	-0.04	146.6	0.07
Eastmid	-390.4	-0.18	-983.8	-0.59			-1900.4	-0.72	-1552.7	-0.60
Westmid	-3443.4	-3.20	-3643.2	-2.84			-3843.8	-1.92	-3713.3	-1.87
Easteng	-2085.2	-1.57	-2935.8	-1.79			-4371.1	-1.74	-4059.0	-1.62
London	450.4	0.28	-1254.0	-0.60			-3614.8	-1.10	-3284.1	-1.02
Southeast	-4050.2	-1.81	-5120.8	-2.71			-6461.5	-2.17	-6244.7	-2.11
Southcent	-6153.5	-3.48	-6944.9	-3.90			-8502.1	-3.06	-8146.1	-2.96
Southwest	-793.4	-0.57	-1042.7	-0.66			-1938.2	-0.78	-1668.9	-0.68
SMRchd	29.13	1.82	18.84	1.04	10.20	0.47	12.87	0.68	14.57	0.77
SMRpulm	-5.42	-0.51	-3.29	-0.28	-2.02	-0.15	-1.35	-0.11	-0.62	-0.05
SMRstrok	14.14	0.84	20.71	1.29	19.92	1.11	20.63	1.28	21.41	1.33
y2005	1622.2	3.23	1487.3	2.75	1254.8	1.66	1472.4	2.65	1498.4	2.75
y2006	1046.5	1.38	698.3	0.91	100.5	0.08	546.2	0.64	637.4	0.78
y2007	3944.5	4.24	3525.6	3.86	2151.1	1.22	2928.4	2.85	3172.0	3.19
y2008	3421.1	2.96	3514.7	3.12	3267.9	1.53	3830.5	3.01	3856.5	3.11
B-P test	143.520									
Hausman			23.820				8.050		2.680	
p-value	0.000		0.251				0.995		1.000	

Note: For variable definition see Appendix 1. OLS = Ordinary Least Square; RE = Random Effect; FE = Fixed Effect; HT = Hausman & Taylor; AM = Amemiya & MaCurdy; Coef = Coefficient; B-P = Breusch-Pagan

In the models that assume all the covariates to be uncorrelated with unobserved individual effects (OLS and RE models), the effect of the number of individuals claiming job seekers' allowance benefits is positive and significant. The variable becomes non-significant after allowing and controlling for endogeneity. The education score is non-significant even after accounting for its potential correlation with the area-specific and time invariant error term. The effect of ethnicity suggests that higher percentage of residents from Asian ethnic groups leads to lower cancer spending when all covariates are assumed to be exogenous, but the effect becomes non-significant when all or part of the explanatory variables are allowed to be endogeneous. In that case, the effect of percentage of Black ethnic residents becomes weakly and positive significantly correlated with cancer expenditure. In terms of the supply indicators, only the number of GPs shows a significant effect in the models that allow for endogeneity suggesting that the larger the number of GPs in the area the lower the spending on cancer treatment. There is some area variation as shown by the significance of some SHA indicators, and the effect of the severity in other disease domains proxied by SMR for CHD, stroke and COPD is found to be non-significant in every model. The year effects suggest that expenditure is increasing over time

The Hausman test for the instrument sets used in the HT and AM estimators appear to be valid, enabling the use of the these models. The Hausman test that compares HT and AM does not reject the extra exogeneity assumption imposed by the AM estimator, which is thus preferred as it is generally more efficient. We focus hereafter on the results from the AM regression model in order to measure inequity in cancer spending across PCTs.

5.2. Equity estimates

Table 2 summarises the equity estimates in cancer spending. The indices of SES-related inequity are measured using the number of job seekers' benefit claimants as the ranking measure, while the need-related indices are computed using the number of cancer cases as the ranking variable. The variables were transformed (100,000 minus actual count) to provide the standard interpretation of the equity estimates, where a negative CI indicates that the variable of interest is concentrated among more deprived/ill health groups.

Horizontal inequity (HI) is measured using the conventional and the conservative approach (Bago d'Uva *et al.*, 2009) the difference between the two being that the later excludes the contribution of the error term from the horizontal inequity estimate. Baseline indices presented in Table 2 employed the combined target group defined by the 70% of PCTs meeting the largest number of the 14 individual targets to measured vertical inequity. When each of the 14 target indicators is used separately to select the PCTs that form the target group the findings were found to show some variation for specific target indicators but the vast majority yield to the same trend as the baseline model (result not shown).

Table 2 presents the results using the long-run approach. The CI_T for actual spending shows that total cancer expenditure is concentrated on areas with larger number of cancer cases as well as areas with larger number of job seeker's benefit claimants. Therefore there is pro-poor and pro-sick allocation of actual cancer expenditure.

The indices of HI suggest that after controlling for the average effect of the need indicators, there is no evidence of statistically significant HI with respect to deprivation and needs. The HI indices are negative (pro-poor) with respect to deprivation and positive (pro-healthy) with respect to needs. The conservative estimates lead to smaller indices of SES-related HI, while

the need-related HI is found to be larger in absolute terms when we exclude the contribution of the error term; both indices remain statistically non-significant.

The VI indices with respect to need and with respect to deprivation are positive, indicating pro-rich and pro-healthy vertical inequity, respectively. The indices are considerably larger with respect to the need dimension than with respect to the SES dimension, but only weakly significant at the 10% significance level.

Table 2. Estimates of inequity in expenditure on cancer programme

	SES-related		Need-related	
	CI	**CI/SE**	**CI**	**CI/SE**
Actual	-0.2252	-18.26	-0.3433	-31.03
Horizontal inequity				
Conventional	-0.0359	-1.46	0.0196	0.65
Conservative	-0.0279	-1.35	0.0213	1.03
Vertical inequity	0.0141	0.34	0.0792	1.69
Total inequity				
Conventional	-0.0220	-0.36	0.0983	1.71
Conservative	-0.0138	-0.25	0.1005	1.81

Note: SES = Socioeconomic Status; CI = Concentration Index; SE = Standard Error.

Standard errors are derived using bootstrapping techniques.

Overall, the index of total inequity with respect to deprivation is non-significant, indicating an equitable distribution of resources across the socioeconomic distribution in cancer spending. The analysis with respect to the need dimension provides some evidence of a pro-healthy total inequity allocation of cancer expenditure across PCTs, but the indices are only statistically significant at the 10% significance level.

5.3. Results from the decomposition analyses

The decomposition approach helps us to understand the mechanisms behind the equity results found in these analyses and are presented in Table 3. Not surprisingly, most of the variation in total cancer spending across both the need and the deprivation distribution is due to differences in the population size of the PCTs. The second largest contributor is in both cases the number of individuals suffering from cancer. The contributions of these two variables are strongly significant. The severity indicators make a modest contribution to the observed inequalities in expenditure, although the contribution of SMR for cancer is found to be significant in explaining variation across the need distribution. The role of the percentage of individuals in different age group is driven by the contribution of the percentage of individuals aged 75 and older. This variable has a positive effect on spending and tend to be concentrated on richer areas but also in areas with larger number of cancer cases, contributing thus to a pro-rich but also to a pro-sick allocation of cancer expenditure. The opposite holds true for the case of the percentage of males in the population.

The contributions of the non-need variables explain the finding with respect to horizontal inequity and are graphically presented in Figure 1. None of the contribution of the individual

non-need factors were found to be statistically significant (see Table 3). In the case of the SES-related HI we found that, at equal level of needs, cancer expenditure was concentrated on poorer areas, and a big fraction of this was due to the contribution of the error term. The next largest contributor is the number of job seekers' claimants. Education scores, ethnicity and the severity in other diseases domains make a small contribution towards the pro-poor HI finding, while the contribution of supply and regional indicators leads to a more pro-rich allocation.

Table 3. Decomposition of inequality in expenditure on cancer across PTCs

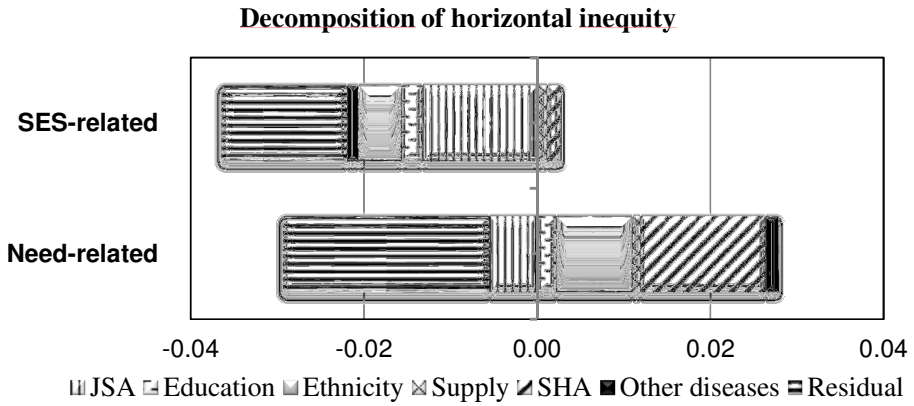
		SES-related				Need-Related			
	Elasticity	**CI**	**Cont**	**Percent**		**CI**	**Cont**	**Percent**	
Cases (transf.)	-3.327	0.008	**-0.027**	12.1%	12.1%	0.014	**-0.046**	13.5%	13.5%
SMRcancer	0.191	-0.011	-0.002	0.9%		0.020	**0.004**	-1.1%	
EQ5Dcancer	-0.087	0.016	-0.001	0.6%	1.5%	-0.024	0.002	-0.6%	-1.7%
Population	0.797	-0.211	**-0.168**	74.8%	74.8%	-0.342	**-0.273**	79.4%	79.4%
Age09p	0.088	-0.004	0.000	0.2%		0.024	0.002	-0.6%	
Age2039p	-0.393	-0.020	0.008	-3.5%		0.059	-0.023	6.8%	
Age4059p	0.047	0.012	0.001	-0.2%		-0.023	-0.001	0.3%	
Age6074p	-0.461	0.014	-0.006	2.9%		-0.062	0.029	-8.3%	
Age75plusp	0.657	0.018	0.012	-5.1%	-5.7%	-0.069	**-0.045**	13.2%	11.4%
Malesp	4.829	-0.001	-0.005	2.4%	2.4%	0.002	0.010*	-3.0%	-3.0%
JSA (transf.)	-0.905	0.015	-0.013	5.9%	5.9%	0.006	-0.006	1.6%	1.6%
IMDeduc	0.035	-0.069	-0.002	1.1%	1.1%	0.061	0.002	-0.6%	-0.6%
Asianp	-0.018	-0.110	0.002	-0.9%		0.261	-0.005	1.3%	
Blackp	0.034	-0.181	-0.006	2.7%		0.319	0.011	-3.1%	
Chinp	0.014	-0.059	-0.001	0.4%		0.133	0.002	-0.6%	
Otheretp	0.004	0.000	0.000	0.0%	2.2%	0.196	0.001	-0.2%	-2.6%
SMRchd	0.045	-0.012	-0.001	0.2%		0.032	0.001	-0.4%	
SMRpulm	-0.002	-0.025	0.000	0.0%		0.069	0.000	0.0%	
SMRstrok	0.064	-0.012	-0.001	0.3%	0.2%	0.002	0.000	0.0%	-0.4%
GPs	-0.177	-0.006	0.001	-0.5%		-0.010	0.002	-0.5%	
GPdistant	-0.010	0.018	0.000	0.1%		-0.151	0.001	-0.4%	
Inpcap	-0.028	0.000	0.000	0.0%		-0.002	0.000	0.0%	
Inpdistant	0.012	0.012	0.000	-0.1%	-0.5%	-0.189	-0.002	0.7%	-0.3%
Northeast	0.000	0.102	0.000	0.0%		0.279	0.000	0.0%	
Yorkshire	0.000	-0.332	0.000	0.1%		-0.130	0.000	0.0%	
Eastmid	-0.004	-0.663	0.002	-1.1%		-0.444	0.002	-0.5%	
Westmid	-0.011	-0.212	0.002	-1.0%		0.043	0.000	0.1%	
Easteng	-0.012	0.098	-0.001	0.5%		-0.239	0.003	-0.8%	
London	-0.013	0.102	-0.001	0.6%		0.442	-0.006	1.7%	
Southeast	-0.014	-0.239	0.003	-1.5%		-0.706	0.010	-2.9%	
Southcent	-0.017	0.126	-0.002	1.0%		-0.284	0.005	-1.4%	
Southwest	-0.005	0.340	-0.002	0.7%	-0.7%	-0.337	0.002	-0.4%	-4.2%
Total					93.3%				93.1%

Note: For variable definition see Appendix 1. SES= Socioeconomic status; CI = Concentration index; Cont = Contribution; Percent = Percentage contribution. Contributions in bold are significant at 5% significance level, contribution with star are significant at 10% level. Standard error s around the contributions are computed using bootstrapping techniques. Cancer cases and job seeker's allowance claimants indicators are transformed by subtracting the actual number to 100,000.

Moving to the need-related HI, we found a small and pro-healthy HI index. Interestingly, this result is not driven by the contribution of the number of job seeker's benefit claimants, as this variable contributes towards a pro-sick HI index. However, all the other non-need indicators

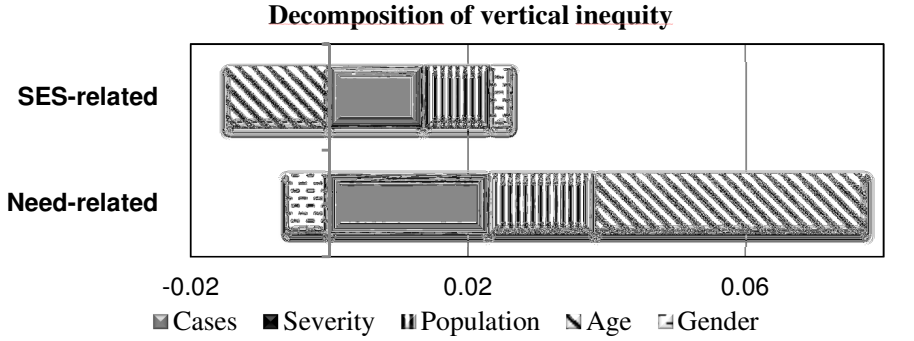
including education scores, ethnicity, supply and regional indicators and severity in other disease domains contributes towards the pro-healthy HI finding. The largest contributor factors are the regional and ethnicity indicators as seen in Figure 1 for the estimated pro-healthy HI.

Figure 1. Decomposition of SES-related and need-related horizontal inequity



The individual contribution of each of the need variables to vertical inequity is represented graphically in Figure 2. The divergence from the estimated and the target effect of the age variables on spending makes the largest contribution to the estimated VI with respect to both need and deprivation rankings, followed by the contribution of the count of cancer cases variable. The role played by the differences in the estimated coefficients of the size of the population and the percentage of males is relative small in explaining the estimated VI.

Figure 2. Decomposition of SES-related and need-related vertical inequity



6. Discussion

The findings of this paper suggest that while cancer spending appears to be equitably distributed across affluent and deprived areas, there is some evidence of inequity favouring healthier regions. The results from this analysis have shown that in the case of SES-related inequity estimates, the inclusion of vertical inequity considerations in addition to horizontal inequity did not affect substantially the final conclusions about socioeconomic-related inequity in the allocation of cancer spending. However, when the need indicator was used as the dimension for the measurement of inequity, vertical inequity was found to be the main driver of observed total inequity in the allocation of cancer spending across the need

distribution. Moreover, the inclusion of the need dimension in addition of the socioeconomic dimension in health care equity investigations was proven to provide valuable information. We show that the equitable allocation found with respect to the deprivation distribution does not necessarily mean that health care resources are being distributed appropriately according to need.

The correlation of the need and deprivation variables is expected, and found to be positive. Therefore one would probably expect the inequity results that measure inequity with respect to the need distribution and with respect to the deprivation distribution to show a similar trend. This is the pattern found for the distribution of actual spending on cancer. However in the case of horizontal inequity, the results suggest that the effect of the non-need variables favour a disproportionally larger allocation towards more deprived areas but also towards areas with lower number of cancer cases. The decomposition analysis sheds some light onto this result highlighting that the other non-need indicators – rather than job seekers' claimants – are responsible for the pro-healthy HI estimate across the need distribution. The role of the number of job seekers' allowance claimants worked on the same direction than in the case of the SES-related horizontal inequity contributing to a more pro-sick distribution as expected. The differences in the magnitude of the consequences of vertical inequity across the need distribution and across the socioeconomic distribution also explained the divergence of the final results. The size of SES-related pro-rich vertical inequity is considerably smaller and not capable of compensating for the pro-poor level of HI inequity found. The large extent of pro-healthy vertical inequity drives the need-related total inequity result.

The major advantages and limitations of analysis that uses national administrative data to identified health care inequalities rather than individual level information is summarised by Cookson et al., 2010. They highlight that the two main advantages are that national administrative information includes almost everyone and everywhere in the country and that are routinely available every year. The main limitations are related with the considerable noise in the data due to ecological fallacies, unobserved geographical factors, and spatial autocorrelations. Appropriate control for variations in needs is possibly the most difficult challenge in investigations using geographical areas as the unit of analysis. Therefore, the aim of our analysis has been to maximise the extent to which variation in needs are captured, and therefore to reduce the impact of unobserved variables that might be driving differences in spending allocations. In our analysis we have tried to do this by including area level variables that capture both the level as well as the severity of cancer cases across regions in addition to using econometric techniques that facilitate the control for unobserved factors that might be correlated with the covariates in our models. However, none of these variables and techniques can offer a perfect substitute for unmeasured individual characteristics. In particular, cancer care has been argued to present many difficulties when assessing inequities. Dixon *et al.*, 2007 highlighted that these '*difficulties include the range of cancers and their aetiology, the impact of screening and the interpretation of case-mix adjustment'*. Furthermore, the econometrics techniques used in our analysis are aimed at controlling for endogeneity with respect to the unobserved individual effects, but they maintain the assumption that the covariates are uncorrelated with the idiosyncratic error disturbance.

Our findings suggest that cancer spending allocation meets the aim of achieving a distribution of health care resources that do not discriminate against areas with different levels of socioeconomic deprivation. However, we find some evidence that health care spending is not appropriately concentrated on areas with larger needs, and this is mainly driven by vertical inequities with respect to the need distribution. Vertical equity implies that individuals with

different levels of need should receive appropriately unequal treatment. This principle of inequity is not captured by the resource allocation formulae used to distribute resources in England and which have traditionally focussed on ensuring 'equal access for equal needs'. However, in more recent times there has been a growing interest in other equity goals. For example, since 1999 a second equity objective has also been pursued in England – to contribute to the reduction of avoidable health inequalities – which was to be considered jointly with the equal opportunity of access objective (Department of Health, 2008). The importance of the focus on vertical equity as a mean to reduce inequalities in health has already been highlighted in the literature (Hauck *et al.*, 2002). Sutton & Lock, 2000 also provided an illustration of incorporating the aim of vertical equity into the resources allocation formulae design in Scotland. However, more work need to be done in order to explicitly consider vertical inequities aspects in the distribution of health care resources. Better measures of needs provided by newly available epidemiological data collected within the Quality and Outcome Framework could provide the possibility of incorporating better indicators of needs. Efforts would nevertheless need to be focussed on identifying the appropriate magnitude of the effect of the need indicators in order to allocate resources appropriately according to variations in needs in different populations.

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Appendix 1. Description and (population-weighted) summary statistics

Name	Description	Mean	SD	Years	Source	Original Geography
Expenditure	Total expenditure on cancer programme (£000)	36,918	20,702	2004/05-2008/09	PBD	PCT
Cases	Cancer cases, counts (excluding non-melanoma skin cancer)	4,333	3,141	2004/05-2008/09	QOF	PCT
SMRcancer	Indirectly SMR from all cancers	102.3	10.940	2004-2008	ONS	PCT
EQ5Dcancer	Cancer severity index	0.720	0.588	Time invariant	HSE	SHA
Population	Total population size	441,283	245,699	2004-2008	ONS	MSOA
Age09p	Population aged 0-9, percentage	11.618	1.178	2004-2008	ONS	MSOA
Age1019p	Population aged 10-19, percentage	12.705	1.050	2004-2008	ONS	MSOA
Age2039p	Population aged 20-39, percentage	27.475	5.718	2004-2008	ONS	MSOA
Age4059p	Population aged 40-59, percentage	26.807	2.259	2004-2008	ONS	MSOA
Age6074p	Population aged 60-74, percentage	13.685	2.559	2004-2008	ONS	MSOA
Age75plusp	Population aged over 75, percentage	7.710	1.618	2004-2008	ONS	MSOA
Malesp	Males, percentage	49.105	0.640	2004-2008	ONS	MSOA
JSA	Job seeker allowance claimants working age group, counts	5,564	2,677	2004/05-2008/09	ONS	LSOA
IMDeduc	Index of deprivation: Education Skills and Training, score	21.592	8.878	2004 & 2007	ONS	LSOA
Whitep	White, percentage	90.362	10.719	2004-2007	ONS	LSOA
Asianp	Asian, percentage	5.475	6.913	2004-2007	ONS	LSOA
Blackp	Black, percentage	2.754	4.319	2004-2007	ONS	LSOA
Chinp	Chinese, percentage	0.729	0.547	2004-2007	ONS	LSOA
Otheretp	Other ethnic, percentage	0.682	0.686	2004-2007	ONS	LSOA
GPs	All Practitioners (head count) per 100,000 population	66.478	8.113	2006-2008	GMS	PCT
GPdistant	Average Road Distance to GP Premises (Km)	1.524	0.698	2004 & 2007	ONS	LSOA
Inpcap	Average capacity at acute providers	213,077	24,198	2004/05	CARAN	MSOA
Inpdistant	Average distance to acute providers	12.790	6.761	2004/05	CARAN	MSOA
Northwest	Strategic Health Authority: North West	0.136	0.343	Time invariant	QOF	N/A
Northeast	Strategic Health Authority: North East	0.050	0.219	Time invariant	QOF	N/A
Yorkshire	Strategic Health Authority: Yorkshire	0.101	0.302	Time invariant	QOF	N/A
Eastmid	Strategic Health Authority: East Midland	0.085	0.279	Time invariant	QOF	N/A
Westmid	Strategic Health Authority: West Midland	0.106	0.308	Time invariant	QOF	N/A
Easteng	Strategic Health Authority: East of England	0.110	0.313	Time invariant	QOF	N/A
London	Strategic Health Authority: London	0.149	0.356	Time invariant	QOF	N/A

Name	Description	Mean	SD	Years	Source	Original Geography
Southeast	Strategic Health Authority: South East	0.083	0.277	Time invariant	QOF	N/A
Southcent	Strategic Health Authority: South Central	0.079	0.269	Time invariant	QOF	N/A
Southwest	Strategic Health Authority: South West	0.101	0.302	Time invariant	QOF	N/A
SMRchd	Indirectly SMR from CHD	114.9	21.561	2004-2008	ONS	PCT
SMRpulm	Indirectly SMR from COPD	102.0	29.539	2004-2008	ONS	PCT
SMRstrok	Indirectly SMR from stroke	110.5	17.522	2004-2008	ONS	PCT
Variables used to selected target groups						
SMRcanc75	Indirectly SMR from all cancers, individuals under 75	100.7	12.8657	2008/09	ONS	PCT
Survbladder	5-year survival rate following diagnosis of bladder cancer	54.589	1.930	2008	ONS	SHA
Survbreast	5-year survival rate following diagnosis of breast cancer	81.478	0.850	2008	ONS	SHA
Survcervical	5-year survival rate following diagnosis of cervical cancer	63.656	1.752	2008	ONS	SHA
Survcolon	5-year survival rate following diagnosis of colon cancer	49.656	1.474	2008	ONS	SHA
Survlung	5-year survival rate following diagnosis of lung cancer	7.244	0.513	2008	ONS	SHA
Survesop	5-year survival rate following diagnosis of oesophagus cancer	10.389	1.244	2008	ONS	SHA
Survprost	5-year survival rate following diagnosis of prostate cancer	77.822	3.075	2008	ONS	SHA
Survstoma	5-year survival rate following diagnosis of stomach cancer	14.689	0.999	2008	ONS	SHA
Compliant62	Compliance with 62-day treatment standard	0.846	0.361	2008/09	CEP	PCT
Reftww	Referrals per 10,000 population through two-week wait	175.1	37.203	2008/09	CEP	PCT
Diagtww	Cancer patients diagnosed through two-week wait referrals,	0.451	0.075	2008/09	CEP	PCT
Screcervical	Cervical cancer screening programme coverage, proportion	0.793	0.036	2008/09	ONS	PCT
Screbreast	Breast cancer screening programme coverage, proportion	0.758	0.070	2008/09	ONS	PCT
Emerlung	Lung cancer diagnoses after emergency admission, proportion	0.287	0.058	2005/06	HES	SHA
Emerpancreas	Pancreas cancer diagnoses after emergency admission, proportion	0.308	0.089	2005/06	HES	SHA
Compet2	World Class Commissioning Competency 2 Level 2 and above	0.948	0.222	2008/09	DoH	PCT
Compet5	World Class Commissioning Competency 5 Level 2 and above	0.729	0.445	2008/09	DoH	PCT
Compet6	World Class Commissioning Competency 6 Level 2 and above	0.442	0.497	2008/09	DoH	PCT

Note: SD = Standard deviation; SMR = standardised mortality ratio; PBD = Programme Budgeting Data; HSE = Health Survey for England; ONS = Office of National Statistics; QOF = Quality and Outcome Framework; GMS = General Medical Services Statistics; HES = Hospital Episode Statistics; CEP = Cancer equality Portal; CHD = coronary heart disease; COPD = Chronic obstructive pulmonary disease, LSOA = Lower Super Output Area; MSOA = Middle Layer Super Output Area; SHA = Strategic Health Authority; PCT = Primary Care Trust; N/A = Not Applicable