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A multilevel model to estimate unavoidable costs and to disentangle allocative inefficiencies of hospital care

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Title:

A multilevel model to estimate unavoidable costs and to disentangle allocative inefficiencies of hospital care

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Abstract: In developing policies to improve the equity and efficiency of systems of health care it is useful to have estimates of the degree of variations in costs of hospital care that are caused by structural characteristics and beyond the scope of local hospital management. The objective of this study was to develop a generalisable model to derive estimates of such costs, which we describe as "unavoidable". This multilevel model estimates total costs per unit of measurable output and identifies different causes of variations in hospital costs by using random intercepts and random slopes. We applied this model to a country with a national health service and identified the existence of diseconomies of scale, and other causes of allocative inefficiencies in centrally-determined distributions of beds and doctors, a lack of local flexibility and systems with perverse incentives.

JEL classification: I19, L32

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1 Introduction

A common objective for the delivery of health services is that this be done equitably and efficiently. Countries with a National Health Service (NHS) often use methods of resource allocation based on a capitation formula to promote geographic equity of access (Rice and Smith, 2001). There is, however, an obvious problem in seeking equity without regard to efficiency or the incentive effects of resource allocation: even if equitable financing were achieved, this would only secure equitable provision if all providers were equally efficient (or inefficient). Although it makes no sense to allocate more resources to populations served by relatively inefficient providers because this generates perverse incentives, there may be various structural causes of inefficiency, beyond the control of local managers, that ought to be taken into account in capitation formulas. Methods used in different countries have, however, frequently not adjusted adequately for such unavoidable costs (UCs), and hence only imperfectly promote equity.

Attempts have been made to account for UCs due to external (mostly) and internal causes (Hutchison et al., 1999) in both community and hospital services. We are concerned in this paper with the latter, for which diverse approaches have been used in different countries, in part because they have been strongly influenced by the characteristics of each country. Examples of UCs on the supply side[2] include:

1. *Costs implied by economies of scale and scope of hospital care.* Scotland is one of the few countries that has adjusted for these with a model that uses a behavioural cost function model (Scottish Office, 1999).
2. *Costs implied by variations in input prices*, because of external market forces or costs of providing services in high cost urban areas (Townsend, 2001). The Netherlands applies regional factors, depending on levels of urbanisation (Rice and Smith, 1999); and England adjusts for differential staff costs, land costs and building costs location (Resource Allocation and Funding Team, 2000).
3. *Costs implied by different mixes on health care provision*, such as the public/private and the primary/secondary care mixes in provision. Australia for

[2] In this context, we disregard literature on UCs on the demand side, such as adjustments to account for relative need (for example, age and sex-related need).

instance, has estimated costs of private provision and deducted these in allocating state budgets for public health care (Rice and Smith, 1999).

4. *Costs implied by delivering hospital care to sparse rural areas*, such as for additional costs of emergency ambulance services. England and Scotland have adjusted for these costs (Townsend, 2001).

Ideally methods of estimating UCs ought to take account of the various possible causes of interactions between them, and disentangle their effects to identify the impact of each cause. Unfortunately, we do not know of any approach that does so. It is common to: estimate the impact of some causes and ignore others; fail to account of interactions, such input prices in estimating economies of scale; and fail to disentangle effects. A further common weakness has been that methods of estimation have made the often unjustifiable assumption that hospitals seek to minimise costs (Cremieux and Ouellette, 2001).

This paper reports the development of a generalisable model to derive estimates of UCs that is designed to be used when methods of (geographical) resource allocation are based on a capitation formula. The application of this model is illustrated for a country with a NHS, namely Portugal. This paper reviews and draws on an extensive literature on cost functions, which covers a variety of subjects: efficiency, economies of scale and scope, and input prices. It proposes a method based on a new approach for adjusting for UCs in hospitals resource allocation that aims to take account of:

1. how different mixes of inputs result in allocative inefficiencies at the level of hospital or hospital group;
2. structural differences in size and scope between hospitals at different levels of the administrative hierarchy;
3. geographic variations; and
4. how payment systems and hospital organisation influence hospital cost structure.

Our approach uses a hierarchical multilevel model of random intercepts and slopes to produce estimates that allow for various estimates of UCs: UCs per unit of measurable output at the hospital level; sources of inefficiencies in the hospital system; and an index of UCs by geographic area. These different kinds of estimates can be used to inform policies that aim to promote both geographic equity of access and efficiency. We believe that this multilevel approach is particularly useful for analysing hospital systems as it is designed to tackle three common characteristics that affect hospital costs: 'compositional' effects (organisation and structure), internal factors (such as local area characteristics), and contextual effects (such as administrative group and hospital location).

The paper is structured into five further sections that briefly review the relevant literature and its implications for estimating UCs; set the context for the development of the model for a NHS; develop the hierarchical and multilevel models; apply the models to Portuguese data and analyse results; and discuss the methods and their wider applicability.

2 Lessons from literature in modelling UCs

Over thirty years ago, Berki (1972) postulated that economies of scale 'ought to exist'. But subsequent reviews of the literature by Vitaliano (1987) showed that there is no agreement on the existence of an optimal size of a hospital and by Aletras et al. (1997) report the extent of economies of scale is not known. McGuire and Hughes (2002) summarised the conflicting conclusions on the existence of economies of scale and show how those conclusions are related to the techniques of estimation used, and in some studies, to methodological flaws. We ought not to be surprised by these findings given the fundamental problem of adequately measuring hospital output. Studies can choose from a multiplicity of variables that can be measured. Many key influences on the behaviour of hospital agents and thus their costs cannot be measured (Vitaliano, 1987). Estimates are sensitive to the use of different methods, functional forms and methodological choices (Folland and Hofler, 2001). It is difficult to disentangle different sources of variation in costs, in particular variations in efficiency (Newhouse, 1994). Thus, eg, in modelling cost functions, many studies have controlled for geographic variations that have been found to be statistically significant (Lave and Lave, 1970) (Grannemann and Brown, 1986) (Vitaliano, 1987) (Zuckerman et al., 1994). But, as these findings have been made without a common framework for treating the influence of geographic and other external variables, such as prices and environment, it is unclear whether these variables are important *per se*, or whether they capture the effects of other confounding variables, which have not been considered.

There have been a number of studies in Portugal that aimed to understand the nature and structure of hospital cost functions, but this literature too is bedevilled by the problems with the general literature on hospital cost functions. Portuguese studies (Paiva, 1993) (Lima, 1998) (IGIF, 1999) (Barros and Sena, 1999) (Carreira, 1999) (Lima, 2000) vary in their objectives and sophistication of techniques. Weaknesses of approaches taken include making the unjustifiable assumption that Portuguese hospitals aim at minimising costs, and failing to control adequately for confounding variables, such as controlling for inputs (such as doctors' salaries). Most studies, however, support the idea that the hospital size needs to be within the range of 200-300 beds to achieve economies of scale (which excludes the largest hospitals providing specialised care).

The general literature gives guidance and identifies issues in the technical requirements of a model and interpretation of results. It is important to control for quality; efficiency; and also, ideally, for the effects of current financing systems on incentives and thus on costs, but it is understood that it is difficult to do this. And it is also essential to recognise that the definition of UCs will vary in the short and the long run.

The following paragraphs draw out from our review of the literature three key choices in developing a generalisable model of hospital costs:

- between stochastic frontier models and data envelopment analysis;
- between an *ad hoc* and flexible cost function models;
- and between specific assumptions of the random components of stochastic frontier models and multilevel models.

The two main approaches to estimating hospital cost functions to identify inefficiency are data envelopment analysis (DEA) and stochastic frontier methods (SFM). DEA computes the frontier practice isoquant (Folland et al., 1997) and give measures of technical inefficiency as distances between the hospital cost and/or output and the frontier. The weaknesses of the DEA method are that it is vulnerable in the presence of outliers (Folland et al., 1997), requires assumptions of economies of scale and does not deal with random variations. SFMs overcome these weaknesses. They estimate the stochastic frontier using econometric modelling, and are based on the microeconomic theory of the firm to link hospital inputs and outputs to costs. As we required a method of estimating UCs without making assumptions on economies of scale, we preferred the SFM approach.

There are two main types of SFMs: *ad hoc* models and flexible cost functions (such as translog models which also have been used in Portugal). Flexible cost models are better than *ad hoc* models in not imposing constraints on the link between inputs, outputs and prices. *Ad hoc* models seem to perform better: in dealing with the decomposition of technical and allocative efficiency; in producing estimates for hospitals in the whole range of the network; and in forecasting costs. As we required a method of estimating UCs for different types of hospitals and of dealing with technical and allocative inefficiency, we preferred an *ad hoc* model.

To produce estimates that disentangle sources of inefficiency, recent studies using SFMs have used fixed and random effects to allow for adjusting the intercepts so that the cost frontier shifts to the appropriate level between groups of hospitals (Linna et al., 1998). However, SFMs have been unable to capture systematic inefficiency (Zuckerman et al., 1994). Another problem with SFMs is that there has been little theoretical guidance on the distributional assumptions used in these models (Linna et al., 1998). Most of these models require strong assumptions that cannot be tested (such as in the technological production function used in some studies) (Newhouse, 1994). We recognise that the approach we use in this paper also suffers from a lack of theoretical guidance on the assumptions of the random components.

Multilevel models, random coefficient models and hierarchical linear models have been used interchangeably and stand for types of statistical models that handle simultaneously (within the same model) the micro-scale of observation units and the macro-scale of contexts (Duncan et al., 1998). SFMs have often used multilevel techniques to decompose the error term into two components of allocative and technical inefficiency. The multilevel framework has been used to analyse data that fall naturally into hierarchical structures. This framework has been applied to analyse geographic variations in health and health care (Subramanian et al., 2001) (Malmstrom et al., 2001), and provider costs and efficiency (Carey, 2000). Several studies have shown the advantages of the multilevel approach over ordinary least squares (OLS) estimation (Rice and Jones, 1997).

In this paper we develop two types of models: the hierarchical fixed effects model (HFEM) and the multilevel model (MLM). As explained below, the two approaches offer a trade-off between satisfying the technical criteria and being transparent. We see our main contribution being the development of the MLM with random intercepts and slopes. Our MLM differs from earlier studies using the SFM approach in three respects. First, studies of incentives using SFMs have used random effects (i.e., random intercepts) for capturing differences in efficiency between types of hospitals. Our MLM uses random intercepts and slopes to identify and capture the mix of inputs that are expected to generate allocative inefficiencies. Second, mainstream SFMs have assumed a positive distribution of the error term structure (error at the hospital level) that implies: covariates capture the frontier/envelope of costs; the errors represent positive deviations from that absolute frontier/envelope and are interpreted as indicators of technical inefficiency. Our multilevel model assumes a normal (not a positive) distribution of the error because of constraints imposed by the software available to estimate multilevel models. Third, our MLM specifically deals with the impact of the hierarchical spatial structure of hospitals on costs.

3 Application to a NHS

The objectives of this paper are to describe a generalisable approach to modelling UCs of wide applicability to any country that satisfies technical criteria and can be used in policies to promote an equitable allocation of resources. Such a model ought to satisfy the following criteria:

- Have a structure that relates to the cost drivers in the system;
- Perform well on statistical grounds;
- Decompose different sources of inefficiency that are expected to be statistically significant.

For the model to be used in a policy to promote an equitable allocation of resources it ought to aim for transparency and avoid creating perverse incentives. The latter means that we need a method to estimate UCs that should not rely upon individual hospital data. Both the HFEM and MLM offer a trade-off between satisfying the technical criteria and being transparent; and both are designed to create estimates that avoid creating perverse incentives.

We illustrate our approach through its specification and application using data from the National Health Service (NHS) in Portugal which has the common structural characteristics of that model: universal coverage, essentially free at the point of delivery, and financed by taxation, and the traditional characteristics of hospitals being owned and run by the state in hierarchical structure. There is a referral system between GPs and hospitals and between hospitals (but there are in practice admissions outside the referral system). The administrative hierarchy of hospitals (from central general to central specialised to district and to level I hospitals) reflects differences in technological complexity, specialised services and human resources, geography and size of catchment areas. Hospitals at the bottom of the hierarchy do not provide all specialties and refer patients to hospitals at the top of the hierarchy.

The centralised system of command and control has been working as follows. Hospital budgets are determined mainly by historical reimbursement and only partly by production levels. There is limited accountability of doctors and administrators, which results in recurrent failures to contain costs, but there are no penalties for systematic budget overruns. There is no charging system for capital costs. There is evidence of inefficiencies caused by hospital administrators lacking power to decide investment and staff. For example, a lack of doctors has constrained the use of beds in smaller hospitals (the converse probably applies in large hospitals). The ratio of nurses to doctors is low and is expected to decrease productivity and increase costs (and thus allocative inefficiency). The high variations in the mix of inputs of doctors/nurses/beds also provide evidence of variations in allocative efficiency across hospitals. Hospital administrators have little control over hospital doctors, who are salaried and enjoy a dual employment status. Doctors have little incentive to be productive in public hospitals, as they generate extra-income in the private sector and by working overtime in the NHS. Doctors located in urban areas tend to have a lower productivity, as they also work in the private sector. The HFEM and MLM are developed to deal simultaneously with Portugal's hierarchical structures of hospitals, sources of inefficiency and geographic variations in hospital costs.

The NHS in Portugal is in a similar position to England in the 1970s at the time of the seminal report of the Resource Allocation Working Party (RAWP) (Department of Health and Social Security (United Kingdom), 1976): there is a general commitment to equity as stated in national policies, but there are substantial inequities (Oliveira and Bevan, 2003). Until very recently, the NHS in Portugal has had centralised systems of command and control that not only failed to provide incentives for efficiency but included some elements that generate perverse incentives. Hence the Portuguese NHS is a particularly interesting case study for the application of our generalisable model. Obviously given these characteristics, in modelling hospital costs, it makes no sense to assume that there is an objective to minimise costs and it is important to develop a model that can identify sources of inefficiency in the system.

4 Stochastic hierarchical models

4.1 Methodological approach

The methods developed in this study are normative in that we use an explicit framework to justify the choice of methodological options (similar to that used by (Soderlund and Jacobs, 2001)). The methods use an integrated approach to model UCs that involves a simultaneous treatment of input prices, inefficiencies, economies of scale and scope and other factors in the model. In this section we summarise the methodological approach and development of the HFEM and MLM models. We describe the common characteristics of each model, outline their distinctive features and strengths and weaknesses. We then give the algebraic specification of each model in the next main sub-section.

Both models use the total cost per unit of measurable output as the dependent variable (afterwards referred to as standardised cost), so as to create a standardised indicator that is compatible across hospitals and across areas. Measurable hospital outputs are defined as inpatient discharges, outpatient attendances and emergency and accident admissions. These are aggregated in an output index that weights inpatient discharges, outpatient attendances and accident and emergency admissions by (total) unit costs per hospital type for each of these outputs.

Both the MLM and HEFM:

- Impose a log-linear or a semi-log relationship between the standardised cost and the covariates (functional relationships as defined in Gujarati (1995)). The logarithmic structure is appropriate as the distribution of standardised costs is expected to be skewed.
- Control for a wide range of variables that impact on standardised costs and account indirectly for the multidimensional nature of output and for the unobserved price of hospital output (given that market mechanisms are very weak and there are no explicit prices).
- Use an *ad hoc* approach that does not derive from a specific assumption of hospital behaviour. In particular, we avoid the requirement of making the assumption that hospitals seek to minimise costs by allowing some covariates to capture inefficiencies or other components of avoidable costs. For example, the models partly attempt to control for inefficiency by controlling for the influence of past hospital decisions and the historical level of funding on hospital costs.
- Aim to explain variations in costs that are avoidable and unavoidable, as represented in Figure 1. UCs are explained by variables that relate to the characteristics of hospital activity that impact on costs and that are outside the scope of management.
- And are developed to integrate the hierarchical structures of geographic location and of administrative types of hospitals. Both assume that there are systematic variations between hospitals from different groups (both in terms of hospital hierarchy and location) and that hospitals within the same group are hypothesised to share a set of characteristics.

The HFEM corresponds to a conventional model to be estimated by traditional OLS, with controls for geographic and hierarchical variations made by the use of fixed effects. This model uses a set of covariates to explain variations in costs (defined above and captured by the vector of covariates), and dummies to control for hospital administrative hierarchy and geographic variations.

The MLM controls for spatial variations through the use of dummies for the geographic area. The MLM makes different assumptions about the error term from those made in OLS regression used by the HFEM to account for intra- and inter-group correlations. The MLM takes into account the composition and the context of each hospital in the network, and uses a multilevel structural classification, in which hospitals as described in (Snijders and Bosker, 1999):

1. Are level-1 units (which represent the lower level unit of analysis, i.e., the hospital). The covariates at this level vary between hospitals and relate to the composition and characteristics of individual hospitals.
2. Belong to one group from the administrative hierarchy, which corresponds to a level-2 unit (which represents one grouping of level-1 units). The covariates at this level relate to the context of hospital care, as captured by structural differences between administrative groups of hospitals;
3. Belong to one geographic area that corresponds to an alternative level-2 unit. The covariates at this level relate to the context of hospital care, as captured by location.

The MLM assumes that the impact of some of the covariates on standardised costs depends not only on the hospital values but also on the characteristics of the administrative group to which the hospital belongs. The model uses random slopes for two covariates –the ratios of nurses/doctors and beds/doctors- and a random intercept as components of allocative inefficiencies. The allocative inefficiencies are defined in the Portuguese context. The remaining covariates (including the geographic) represent the same variations as in the HFEM model.

The MLM is better than the HFEM in terms of its theoretical structure, its approach in decomposing sources of inefficiency, and its greater reliance on group data. The HFEM is better in terms of being more transparent but has a fundamental weakness: it relies on dummies to control for the administrative classification of the hospital. It is expected that on statistical grounds, the MLM will perform better than the HFEM.

4.2 The models

4.2.1 General structure

The basic notation in use is as follows. Index i is taken as the key hospital identifier. i and i' stand for different hospitals ($i \neq i'$). Any hospital i belongs to a hospital administrative group j and a geographic area k (that is, j and k depend on i: $j(i)$ and $k(i)$), so the indices j and k are omitted for hospitals in some of the equations given below. l is the type of hospital in the statistical definition of costs (which often differs from the administrative classification).

Equation 1 is the index of hospital output ($OutputIndex_i$) that weights inpatient discharges ($Disch_{il}$), outpatient attendances ($Outpat_{il}$) and accident and emergency admissions ($Emerg_{il}$) of hospital i by unit costs for each type of hospital (each hospital belonging to hospital group l). a_l, b_l and c_l are average total unit costs from hospitals of type l, for inpatient discharges, outpatient attendances and emergency and accident admissions.

$$OutputIndex_i = \sum_l \left[\frac{Disch_{il} * a_l + Outpat_{il} * b_l + Emerg_{il} * c_l}{a_l + b_l + c_l} \right] \tag{1}$$

Equation 2 is the standardised cost ($COutput_i$) and is derived from the ratio of the total cost of hospital i ($TotCost_i$) to the index of hospital output ($OutputIndex_i$).

$$COutput_i = \frac{TotCost_i}{OuputIndex_i} \tag{2}$$

Equation 3 is the relationship between the natural logarithm of standardised cost ($\ln(COutput_{ijk})$) and a linear function of the covariates. x_{ijk} are the explanatory variables vector for standardised costs, which contains two sub-sets of variables that have a log-linear and a semi-log function relationship with the dependent variable. e_{ijk} is the random error.

$$\ln(COutput_{ijk}) = C_{ijk}(x_{ijk}) + e_{ijk} \tag{3}$$

The two models we use (HFEM and MLM) make different assumptions about the structure of the error (e_{ijk}) and the association between hospital characteristics and standardised costs.

4.2.2 HFEM- Hierarchical Fixed Effects Model

Equation 4 gives the structure of the HFEM. The model uses a set of covariates to explain variations in costs (captured by the vector x_{ijk}), and dummies to control for hospital administrative hierarchy (t_{ij}s) and for geographic location (g_{ik}s). α_0, α_1 are coefficients of the fixed part of the HFEM (excluding the geographic and hospital group related coefficients). α_{2k} are fixed coefficients for dummies of the geographic area k (geographic related coefficients). α_{3j} are fixed coefficients for dummies of the administrative group j. e_{ijk}^{HFEM} is the random error for the HFEM that follows the classic assumptions.

$$\ln(COutput_{ijk}) = \alpha_0 + \alpha_1 * x_{ijk} + \sum_k (\alpha_{2k} * g_{ik}) + \sum_j (\alpha_{3j} * t_{ij}) + e_{ijk}^{HFEM} \tag{4}$$

4.2.3 MLM- Multilevel Random Intercepts and Slopes Model

Equations 5 and 6 define the MLM. Equation 5 gives the groups of determinants of the MLM. This model uses random slopes for two covariates, the ratios of nurses/doctors (β_{1j}) and beds/doctors (β_{2j}) and a random intercept (β_{0j}) as components of allocative inefficiencies. d_{ij} is the numbers of doctors. n_{ij} is the number of nurses. b_{ij} is the number of beds. β_{0j} is the random coefficient of the random intercept of the MLM, defined at the hospital administrative group level. β_{1j} and β_{2j} are random coefficients of the nurses to doctors and beds to doctors ratios (respectively) and are the random slopes of the MLM, defined at the hospital administrative group level. e_{ijk}^{MLM} are random errors at the hospital level of the MLM model. β_3 is the set of coefficients of the variables at the hospital level and is deterministic. β_{4k} are fixed coefficients for dummies of the geographic area k (geographic related coefficients to be interpreted in the same way as in the HFEM). The remaining covariates (x_{ijk} and g_{ik}) represent the same variations as in the HFEM model.

$$\ln(COutput_{ijk}) = \beta_{0j} + \beta_{1j} * \left(\frac{n}{d}\right)_{ij} + \beta_{2j} * \left(\frac{b}{d}\right)_{ij} + \beta_3 * x_{ijk} + \sum_k (\beta_{4k} * g_{ik}) + e_{ijk}^{MLM} \quad (5)$$

Equation 6 gives the same model, making the split between deterministic and random components explicit. Equations 6a-c decompose the random coefficients into a deterministic and a random component. β_0, β_1 and β_2 are coefficients of the fixed/deterministic part of the cost model (excluding geographic-related and hospital related coefficients). μ_{0j} is the random component of the random intercept of the MLM, defined at the hospital administrative group level. μ_{1j}, μ_{2j} are random components of the random slopes of the MLM, defined at the hospital administrative group level.

$$\begin{aligned} \ln(COutput_{ijk}) = &\left[\beta_0 + \beta_1 * \left(\frac{n}{d}\right)_{ij} + \beta_2 * \left(\frac{b}{d}\right)_{ij} + \beta_3 * x_{ijk} + \sum_k (\beta_{4k} * g_{ik})\right] + \\ &+ \left[\mu_{0j} + \mu_{1j} * \left(\frac{n}{d}\right)_{ij} + \mu_{2j} * \left(\frac{b}{d}\right)_{ij} + e_{ijk}^{MLM}\right] \end{aligned} \quad (6)$$

With:

$$\beta_{0j} = \beta_0 + \mu_{0j} \quad (6a)$$

$$\beta_{1j} = \beta_1 + \mu_{1j} \quad (6b)$$

$$\beta_{2j} = \beta_2 + \mu_{2j} \quad (6c)$$

The proposed model assumes that the distribution of the random elements follow normal distributions (Equations 7a-d). $\sigma^2_{\mu 0}$, $\sigma^2_{\mu 1}$, $\sigma^2_{\mu 2}$ are variances of the random components of the model at the group level. $\sigma^2_{\mu 0}$ is the variance of the random component of the intercept, while $\sigma^2_{\mu 1}$ and $\sigma^2_{\mu 1}$ is the variance of the random component of the slopes. σ^2_{e0} is the variance of the error term at the hospital level.

$$\mu_{0j} \approx N(0, \sigma^2_{\mu 0}) \tag{7a}$$

$$\mu_{1j} \approx N(0, \sigma^2_{\mu 1}) \tag{7b}$$

$$\mu_{2j} \approx N(0, \sigma^2_{\mu 2}) \tag{7c}$$

$$e^{MLM}_{ijk} \approx N(0, \sigma^2_{eo}) \tag{7d}$$

The model also makes assumptions about the covariance structure (Equations 8a-f). $\sigma_{\mu 0 \mu 1}$, $\sigma_{\mu 0 \mu 2}$, $\sigma_{\mu 1 \mu 2}$ are a set of covariances between the random components, defined at the group level. Covariances between the level 2 random components and the level 1 error are null (8a); covariances between random components and covariates without random slopes are also null (8e-f). Covariances between level 2 random components are estimated within the model (8b-d).

$$\mathrm{cov}(\mu_{0j}, e^{MLM}_{ijk}) = \mathrm{cov}(\mu_{1j}, e^{MLM}_{ijk}) = \mathrm{cov}(\mu_{2j}, e^{MLM}_{ijk}) = 0 \tag{8a}$$

$$\mathrm{cov}(\mu_{0j}, \mu_{1j}) = \sigma_{\mu 0 \mu 1} \tag{8b}$$

$$\mathrm{cov}(\mu_{0j}, \mu_{2j}) = \sigma_{\mu 0 \mu 2} \tag{8c}$$

$$\mathrm{cov}(\mu_{1j}, \mu_{2j}) = \sigma_{\mu 1 \mu 2} \tag{8d}$$

$$\mathrm{cov}(e^{MLM}_{ijk}, x_{ij}) = \mathrm{cov}(\mu_{oj}, x_{ijk}) = \mathrm{cov}(\mu_{1j}, x_{ijk}) = \mathrm{cov}(\mu_{2j}, x_{ijk}) = 0 \tag{8e}$$

$$\mathrm{cov}(e^{MLM}_{ijk}, g_{ik}) = \mathrm{cov}(\mu_{oj}, g_{ik}) = \mathrm{cov}(\mu_{1j}, g_{ik}) = \mathrm{cov}(\mu_{2j}, g_{ik}) = 0 \tag{8f}$$

Equations 9 and 10 give the derived structure of variance and covariance (between two hospitals in the same administrative group) of the MLM. These equations show how the variance and the covariance depend both on the individual and group values.

$$\operatorname{var}\left[\ln(COutput_{ijk})\right]=\sigma^2_{\mu 0}+\left(\frac{n}{d}\right)^2_{ij}*\sigma^2_{\mu 1}+\left(\frac{b}{d}\right)^2_{ij}*\sigma^2_{\mu 2}+2*\left(\frac{n}{d}\right)_{ij}*\sigma_{\mu 0\mu 1}+$$
$$+2*\left(\frac{b}{d}\right)_{ij}*\sigma_{\mu 0\mu 2}+2*\left(\frac{n}{d}\right)_{ij}*\left(\frac{b}{d}\right)_{ij}*\sigma_{\mu 1\mu 2}+\sigma^2_{e0} \quad (9)$$

$$\operatorname{cov}ar\left[\ln(COutput_{ijk}),\ln(COutput_{i'jk})\right]=\sigma^2_{\mu 0}+\left(\frac{n}{d}\right)_{ij}\left(\frac{n}{d}\right)_{i'j}\sigma^2_{\mu 1}+$$
$$+\left(\frac{b}{d}\right)_{ij}*\left(\frac{b}{d}\right)_{i'j}*\sigma^2_{\mu 2}+\left[\left(\frac{n}{d}\right)_{ij}+\left(\frac{n}{d}\right)_{i'j}\right]*\sigma_{\mu 1\mu 0}+ \quad (10)$$
$$+\left[\left(\frac{b}{d}\right)_{ij}+\left(\frac{b}{d}\right)_{i'j}\right]*\sigma_{\mu 2\mu 0}+\left[\left(\frac{n}{d}\right)_{ij}*\left(\frac{b}{d}\right)_{i'j}+\left(\frac{b}{d}\right)_{ij}*\left(\frac{n}{d}\right)_{i'j}\right]*\sigma_{\mu 1\mu 2}$$

5 Empirical models and results

This section describes the data, variables and sample characteristics, gives the results from the estimation of the models and the estimates of UCs per hospital group. It concludes with estimates of a relative index of UCs at the geographic district level.

5.1 Data, variables and estimation techniques

The database consists of 1998 data on: cost, expenditure and production (IGIF, 2000); and an index of purchasing power at the small area level (INE et al., 2000). The database covers 88 public hospitals. Table 1 gives the set of independent variables at the hospital level that were included in the right hand side of the estimated models; and contains brief indications about the concept that each variable attempts to capture.

We developed the sets of models with the following assumptions and characteristics:

1. We assumed that hospital output (including case complexity) is adequately captured by three sets of variables: the output index (the independent variable), the case-mix index and length of stay (covariates in the right hand side of Equations 4, 5 and 6).

2. We classified hospitals following the hierarchical structure by administrative group in Portugal: central general hospitals, central specialised hospitals (including cancer centres), district hospitals and level I hospitals.
3. We had no variables to act as proxies for quality, technology and cost of capital because of the lack of good data.
4. We used the number of doctors as a proxy for hospital size because doctors constrain the use of hospital resources in Portugal and are closely associated with productive capacity (Oliveira and Bevan, 2001).
5. We classified hospitals into eight geographical areas: north coast (includes Porto, Braga and Viana do Castelo districts); north interior (Vila Real, Bragança); centre coast (Aveiro, Coimbra, Leiria); centre interior (Viseu, Guarda, Castelo Branco); south coast (Lisboa, Setúbal); south interior (Santarém); Alentejo (Beja, Évora, Portalegre) and Algarve (Faro).
6. We included controls for revenues from hospital production to the private sector (these estimates need to be interpreted with caution because although hospitals are supposed to charge private insurers or subsystems for their services, they often do not do so).

The HFEM was estimated by GLM, using an identity link function with the natural logarithm of the standardised cost as the dependent variable. This model produces similar coefficient estimates to OLS estimation but generates statistics that are directly comparable with the results of the MLM[3]. The HFEM was estimated using STATA statistical software (Stata Corporation, 2001) and conventional tests for GLM models[4]. The MLM model was estimated using MLWin software (Rasbach et al.,

[3] The alternative would be the use of GLM with a log link and the use of the standardised cost as the dependent variable, but using this technique would produce results not comparable with outputs estimated by the MLM model. Using GLM enables estimates to be produced of values in the original scale and of the loglikelihood of the model. The software package in use for the MLM model does not offer the possibility of carrying out GLM estimation with a log-link function, which would be the ideal estimation technique.

[4] The following econometric tests were applied: specification, goodness of fit, properties of residuals (including deviance) and linktest. The choice between alternative models was based on three criteria: predictive power, parsimony and expected sign of coefficients. Robust estimates of the variance of the estimators have been used (Huber-White estimates of the variance-covariance matrix).

2000) and the restricted (or residual) maximum likelihood estimation[5] (the corresponding algorithm is the restrictive iterative generalized least squares). Hypothesis testing on single parameters and on specification were carried using the tests suggested by the literature (Snijders and Bosker, 1999)[6]. Statistical comparisons of goodness of fit and specifications between the HFEM and the MLM used an adapted version of the Akaike Information Criteria (AIC), in the version suggested in the MLWin software guide (Rasbach et al., 2000): under this version, the model with the smallest AIC should be chosen, and the AIC is equal to the sum of the ln(likelihood) statistic with double the number of parameters estimated in the model.

5.2 Results and analysis

The descriptive statistics of the variables included in the model show systematic differences between hospital administrative groups (although these vary within groups): standardised costs are higher for central and specialised hospitals and lower for level I hospitals; general and specialised hospitals have more complex case-mix, and general hospitals have higher levels of length of stay; case-mix and length of stay are correlated with cost per unit of output; and large and central hospitals are located in areas with higher purchasing power. Other findings are: occupancy rates are higher for central and general hospitals; larger hospitals have both higher proportions of consumption costs as a proportion of total hospital costs (hospital consumption includes drugs and clinical products) and higher outsourcing per unit of output; the proportion of personnel costs to total costs is inversely related to hospital size; and

[5] This method only differs from that of maximum likelihood estimation in the computation of variance and covariance parameters, and produces estimates with less bias (Snijders and Bosker, 1999). Nevertheless, it is preferable to test using likelihood ratios generated by maximum likelihood estimation than to carry out tests on deviance (Snijders and Bosker, 1999).

[6] These included: Wald test for hypothesis involving fixed parameters and likelihood ratio test for hypothesis involving random-effect parameters (for nested models). Residuals were checked for homoscedasticity and specification: analysis of standardised residuals (with variance equal to one); analysis of plots of standardised residuals for individual hospitals against fitted values or level one variables to check model specification and homoscedasticity; analysis of plots of level two residuals against fitted values or level two variables allowed for control of level two variance; residuals at level one and at level two were compared; and the model was checked for the impact of outliers.

smaller hospitals have higher ratios of nurses to doctors, beds to doctors and other employees to doctors.

Common results to the HFEM and MLM are:

- Case-mix, outsourcing per level of output, the relative weight of consumption in the costs structure and personnel costs per doctor increase standardised costs. The impact of outsourcing and consumption on standardised costs tends to reflect previous systems of finance based on historical reimbursement (which means that there are no incentives to seek efficiency). As expected, higher occupancy rates reduce standardised costs; but this result should be treated with caution as the occupancy rate might capture variations in quality or efficiency or economies of scale. We discuss these issues further below.
- The number of doctors increases standardised costs. This is an indicator of diseconomies of scale with hospital capacity. This finding is consistent with previous studies using *ad hoc* specifications, namely that small hospitals experience economies of scale, and large hospitals experience diseconomies of scale (McGuire and Hughes, 2002).
- Growth in past levels of expenditure do not explain current levels of standardised costs.

The HFEM is shown to be statistically highly significant (last column of Table 2): the corresponding R^2 statistic from the OLS estimation is 91.5%. Comparison of the HFEM and MLM models using the AIC shows that the MLM is statistically superior and it is better at modelling allocative inefficiency and differences between hospital groups in the MLM. For the MLM, the coefficients of the variables denoting ratios of nurses to doctors and beds to doctors were found to be statistically significant, which differs from the results of the HFEM. This is as expected as the MLM has better properties than the HEFM on theoretical grounds and accounts more adequately for differences between hospital types.

Table 2 shows the estimates generated by the two models. The results need to be interpreted with caution because of lack of controls for variables, such as quality; hospital output may not capture adequately case-mix and length of stay (McGuire and

Hughes, 2002); and random intercepts and slopes might also capture systematic variations in technical inefficiency.

Important results from the estimation of the MLM are presented in columns A-D in Table 2. In these models, model A has the fewest controls and model D is the most complete, each successive model adds to the controls of the previous model. In model A variation is solely explained in terms of group and hospital level variation; model B adds control for case-mix; model C adds controls for complexity, including all the variables at the hospital and at the hospital group levels and the random components of the MLM; and model D adds controls for geographic variables (using dummies). Model D is the most complete MLM model.

Analysis of results shows:

- Model A: 76% of the random variation is explained by group variation (and the remaining 24% at the hospital level). This corresponds to a random intercepts multilevel model where the intra class correlation is computed as the ratio $\rho = \sigma_{u0}^2 / (\sigma_{u0}^2 + \sigma_{e0}^2) = 76\%$ (Snijders and Bosker, 1999) and can be interpreted as the proportion of total variation of the dependent variable that is explained by the group level (e.g. by the administrative classification). This analysis shows the crucial importance of hospital group factors on hospital costs and, of the use of random intercepts to identify their impact. The use of random slopes implies that the coefficient ρ cannot be analysed because it will depend on specific sample values and on the groups to be compared.
- Model B: the new level of random variations explained by group level variation is 73.3% ($\rho = 73.3\%$). This means that (as expected) variations in case-mix are closely associated with hospital group.
- Model C: as expected, additional controls for hospital complexity (such as outsourcing level per unit of output) reduce the importance of the control for the case-mix index. There are changes in the statistical significance of the ratios of inputs in the HFEM and MLM, which are analysed below. Other hypothetical variables specific to the MLM are statistically significant (as expected) and these have an interpretation very similar to model D and are explained below.

- Model D[7]: two regions with low accessibility to hospital care have higher levels of costs –the Alentejo and the interior North regions-, which suggests that there are higher marginal costs incurred in delivering hospital care to rural populations.

The MLM uses random intercepts and random slopes to account for inter- and intra-group variation, which results in the ratios of nurses to doctors and of beds to doctors ($\hat{\beta}_1$ and $\hat{\beta}_2$ from equations 6a and 6b) becoming statistically significant (this result differs to the HEFM). The MLM shows, firstly that rural hospitals with a higher ratio of beds to doctors have lower standardised costs, which may be due to their lower levels of technology and staff. The second finding is that a higher ratio of nurses to doctors results in increased standardised costs and suggests that where this ratio is higher than average, it is difficult to use nurses efficiently.

In the MLM, the random intercept for hospital administrative group ($\hat{\beta}_{0j}$ from Equation 6a) and the random slope for the beds to doctor ratio (the $\hat{\mu}_{2j}$ component of $\hat{\beta}_{2j}$ in Equation 6c) were found to be statistically significant, but the random slope for the nurses to doctor ratio was not (the $\hat{\mu}_{1j}$ component of $\hat{\beta}_{1j}$ in Equation 6b). This means that the impact of the ratio beds to doctors on costs depends on the hospital group, but the impact of the ratio nurses to doctors does not vary by hospital group. We discuss below more detailed analysis of the findings on random coefficients.

In order to interpret the random estimates, we assume that random slopes and random intercepts capture variations in allocative efficiency but this may hide systematic inefficiencies common to all hospitals. We assumed that residuals fully capture technical inefficiency. Lower and negative values of the random parameters might be

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[7] It is worth making two additional observations on the results of the MLM model (model D). First, it has a high level of covariance between the random coefficients, which is higher than the product of the variances. Although this may appear to be a remarkable result, Snijders and Bosker (Snijders and Bosker, 1999) explain how this is to be expected. Second, the deviance, computed as -2*ln(likelihood), has a negative value. The negative value is explained as follows: the likelihood is a function of the probabilities and for some type of distribution the probability density function may be greater than one (when the dependent variable is continuous), and thus the loglikelihood can be positive.

interpreted as indicating increased efficiency, as they represent a negative influence on standardised costs.

Average estimates of allocative inefficiency of the group level and for the hospital level residuals are shown in Table 3 (though these are very approximate). Empirical results suggest the following:

- *Hospital level random component (e_{ijk}^{MLM}).* The three largest hospitals are performing well[8].
- G*roup level random slopes* (Figure 2). The impact of the ratio beds to doctors is greatest for district and level I hospitals (Table 3).
- *Group level random intercepts* (Table 3). General hospitals are the most inefficient and are followed by specialised hospitals, while level I hospitals are the most efficient.

5.3 Unavoidable costs and geographic redistribution

Residuals for each hospital are assumed to be avoidable costs. Applying the two criteria for defining UCs, the components of the MLM model that are classified as unavoidable are:

- The random intercepts and the ratio beds to doctor (with the random slope) are a source of allocative inefficiency and thus a UC outside local control (although in the long run policies should aim to reduce these costs).
- The dummies capturing geographic variations are costs outside local control.
- For three variables, we chose as benchmark the lowest value within each hospital group, with values in excess being accounted as avoidable. These three variables are: consumption costs over total costs, outsourcing levels per unit of output, and personnel costs per doctor (these variables are influenced by the current financing system).
- For all the other deterministic covariates, 100% of their value is considered UC and thus they are classified as outside local control of hospital managers.

[8] These data are available from the authors.

Summing these components to the national level gives the estimate that, in 1998, 78% of the national hospital costs were unavoidable. This means that if the UCs estimates were used in a resource allocation formula, 78% of hospital costs would be ‘protected’ with the resource allocation system. How information on UCs is used within a system seeking greater equity through the use of a capitation formula generates a complex mix of potential combinations. In the simplest case, when there is equity in utilisation but variation in costs, then information on UCs can be used directly in changing allocations to make them more equitable: the principle would be that hospitals, over time, could be funded for their unavoidable costs. In practice, it is more complex as inequities in funding arise from variations in utilisation and avoidable costs: hence, e.g. an area with low utilisation and high avoidable costs might gain or lose resources depending on the extent of these differences from the norms being used. Figure 3 contains the UC per output at the hospital level, standardised by the national level of UC per output. It shows general and specialised hospitals would have their finance ‘protected’, while level I hospitals would lose funding. This is clarified in Table 4: on average, general and central hospitals have standardised costs 23% above the national average, while level I hospitals are 26% below the national average, which implies significant redistribution between these types of hospital.

An UCs index for the Portuguese district level weights the estimated unavoidable standardised costs for each hospital of the district by the hospital size, when size is proxied by the number of doctors (Equation 11). Estimates of the UCs index at the district level - UC_d - are computed using index of unavoidable standardised costs at the hospital level - $UCOutput_i$ -, where index d represents the geographic district level:

$$UC_d = \frac{\dfrac{\sum_{i \in d} \left(UCOutput_i * d_i \right)}{\sum_{i \in d} d_i}}{\dfrac{\sum_{i} \left(UCOutput_i * d_i \right)}{\sum_{i} d_i}} \qquad (11)$$

The redistribution suggested by the UC index increases relative shares for urban areas with large concentration of supply and decreases shares of resources for areas with the smallest hospitals. Values above 100% in Figure 4 show that the UC index for the district is above the national average, and that if the index were to be used for redistribution, these districts (with costs above 100%) would be 'net' winners from redistribution. District values reflect two elements: the UC index (which implies higher than average shares of the largest hospitals) and the characteristics of the district hospital system. The UC index for Coimbra, Lisboa and Porto are 28%, 13% and 11% above the national average, respectively; and for Aveiro, Leiria and Guarda, 25%, 26% and 32% below the national average. The higher value for Coimbra reflects a hospital structure dominated by large hospitals; the comparative lower value for Lisboa and Porto reflects a mix of large and small hospitals. The district index implies a significant level of redistribution within a capitation formula: 68% to 128% (Figure 4). Hence, the model we developed to inform a policy to promote equity has identified major obstacles to efficiency, for which policies ought to be developed.

6 Discussion

Results have suggested that for Portugal, in the short term, 78% of national costs ought to be protected within a resource allocation system dealing with UCs, but policies ought to be developed to change the structural characteristics that cause allocative inefficiencies. Current incentives (such as financing partly based on retrospective reimbursement) are perpetuating inefficiency in the system in both the short and long run.

Key findings of the model are: there are diseconomies of scale with hospital size (this is in agreement with literature using *ad hoc* cost functions (McGuire and Hughes, 2002)); costs reflect previous systems of hospital finance based on historical reimbursement (for example, levels of consumption and outsourcing); rural regions with lower levels of accessibility have higher costs, *ceteris paribus*; the ratio of inputs (beds/doctors/nurses) impact on costs in ways that vary between hospital groups; there are systematic differences in costs for different groups of hospitals.

Further methodological work on the multilevel model for Portugal could:

- Use a multilevel model with the assumption of a positive distribution of hospital level residuals, to compute the efficient frontier/envelope and develop a model using the microeconomic theory of the firm;
- Focus on the relationship between occupancy rates, staffed beds, and spare capacity to cope with fluctuations in demand for hospital care. For example, it is expected that occupancy rates are inversely related to inefficiency (Zuckerman et al., 1994), occupancy rates might be seen as elements of economies of scale but this is difficult to capture (Scott and Parkin, 1995) and might also be related to unpredictable demand, as large hospitals benefit from lower reserve margin requirements (Aletras et al., 1997).

This study has proposed a new method based on a multilevel model for the estimation of UCs. The multilevel model was designed to deal with systematic variations in costs across administrative groups of hospitals, geographic variations of hospital costs, and the decomposition of allocative inefficiencies (distinguishing between human and capital resources). We recognise that the multilevel approach requires arbitrary assumptions to be made on the distribution of the error and omitted variable bias, and strong assumptions to be made on the independence between the two components of allocative and technical inefficiency (in common with other econometric methods). UCs were computed so as to avoid perverse incentives. Different countries have defined UCs in different ways and this must always be a matter of judgement and what is and is not "avoidable" will depend on the time period chosen. We have proposed criteria for defining UCs and sought to use these in deriving our estimates. The multilevel model with random intercepts and slopes has advantages over other methods and was shown to perform well. We suggest that this model is worthy of consideration in countries using capitation formulae to promote equity.

Tables

Table 1: Variables at the hospital level

Variable	*Purpose*
Case-mix index	Heterogeneity/complexity output and effective demand parameters.
Length of Stay	Complexity output and demand parameters.
Occupancy rate	Managerial use of beds, incentives and constraints imposed by mix of resources.
Number of doctors	Hospital size and input.
Ratio nurses to doctor	Input mix.
Ratio beds to doctor	Input mix.
Ratio other employees to doctor	Input mix.
Consumption costs as a percentage of total costs and/or consumption costs per unit of production	Intermediate input mix and intermediate input price.
Outsourcing costs as a percentage of total costs and/or outsourcing costs per unit of production	Intermediate input mix and intermediate input price.
Personnel costs as a percentage of total hospital cost and/or personnel costs per unit of production	Input mix and input price.
Other costs (apart from consumption, outsourcing or personnel costs) as a percentage of total hospital cost and/or other costs per unit of production	Input mix and input price.
Purchasing Power Index of the area where the hospital is located	Input prices.
Non-NHS revenue as a percentage of hospital revenue	Proxy for other output (work for the private sector).
Number of specialties available	Complexity of output and other hospital outputs.
Dummy for teaching activity	Other hospital outputs.
Growth in hospital expenditure in the last two years	Reflects payment systems for hospital managers, given hospital finance mostly by historical reimbursement.
Overtime payments to doctors/nurses/others, divided by the number of doctors	Reflects system of incentives for management and doctors and nurses, as well as constraints imposed by the current level and mix of resources.

Table 2: Coefficient estimates of the HFEM and MLM

	A	*B*	*C*	*D*	*HFEM*
	No covariates	Control for case-mix	All covariates except geographic	All covariates	All covariates
Ln (casemix)		0.719 (0.09392)***	0.300 (0.06777)***	0.340 (0.065)***	0.264 (0.089)***
Ln (occupancy rate)			-.520 (0.08664)***	-0.500 (0.082)***	-0.380 (0.102)***
Ln (personnel costs per doctor)			0.611 (0.08446)***	0.619 (0.078)***	0.436 (0.107)***
Consumption over total costs			0.012 (0.00231)***	0.012 (0.002)***	0.013 (0.002)***
Ln (outsourcing per unit output)			0.466 (0.05907)***	0.406 (0.060)***	0.526 (0.048)***
Ln (doctors)			0.093 (0.02351)***	0.096 (0.022)***	0.070 (0.025)***
Ln (nurses per doctor)			0.251 (0.06091)***	0.233 (0.058)***	
Dummy Algarve					0.125 (0.064)*
Dummy Alentejo				0.128 (0.062)**	
Dummy interior north				0.136 (0.050)***	0.010 (0.046)**
Constant	6.067 (0.13900)***	6.020 (0.10201)***	0.112 (0.880) (*)	0.219 (0.819)(*)	1.051 (1.389)(*)
Dummy District					-0.209 (0.055)***
Dummy Level I					-0.239 (0.082)***
Ln (beds per doctor)			-0.124 (0.06875)**	-0.135 (0.069)**	
$\sigma^2_{\mu 0}$	0.203 (0.09394)	0.107 (0.05024)	0.0013 (0.0016)	0.0016 (0.0014)	
$\sigma^2_{\mu 2}$			0.0181 (0.0103)	0.0212 (0.0112)	
$\sigma_{\mu 0 \mu 2}$			0.0058 (0.0033)	0.0071 (0.0035)	
σ^2_{e0}	0.064 (0.01035)	0.039 (0.00634)	0.0125 (0.002)	0.0111 (0.0018)	
-2*ln(likelihood)	36.99	-8.73	-121.88	-133.13	-114.8

***- Statistically significant at 1% level; ** -Statistically significant at 5% level; *- Statistically significant at 10% level; (*)- Not statistically significant.

Table 3: Average of allocative inefficiency estimates and hospital level residuals variations at the group level (average residuals, random intercepts and random slopes)

	Average hospital level residual	*Average random intercept*	*Average random slope for the ratio beds to doctor*
General hospitals	0.024	0.037	0.029
Specialised hospitals	0.032	0.019	0.046
District hospitals	-0.012	-0.025	-0.129
Level I hospitals	0.008	-0.042	-0.125

Table 4: UC per output, as a percentage of national UC per output

	Unavoidable costs per output
General hospitals	123%
Specialised hospitals	114%
District hospitals	85%
Level I hospitals	74%

Figures

Figure 1: Decomposition between avoidable and unavoidable costs for each group of hospitals

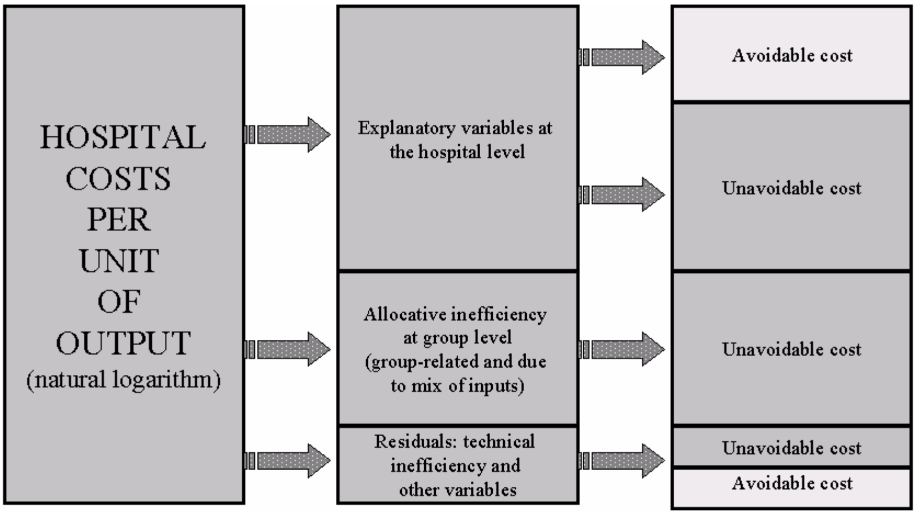


Figure 2: Allocative inefficiency –random slopes coefficients for the ratio beds to doctor

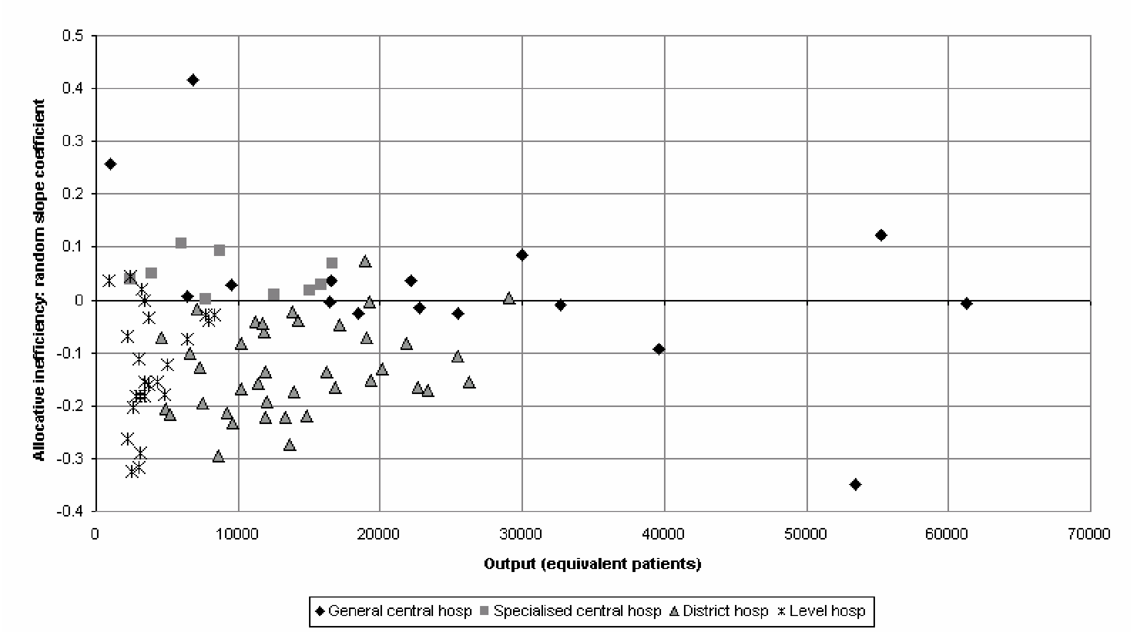


Figure 3: Individual hospital 'winners' and 'losers'

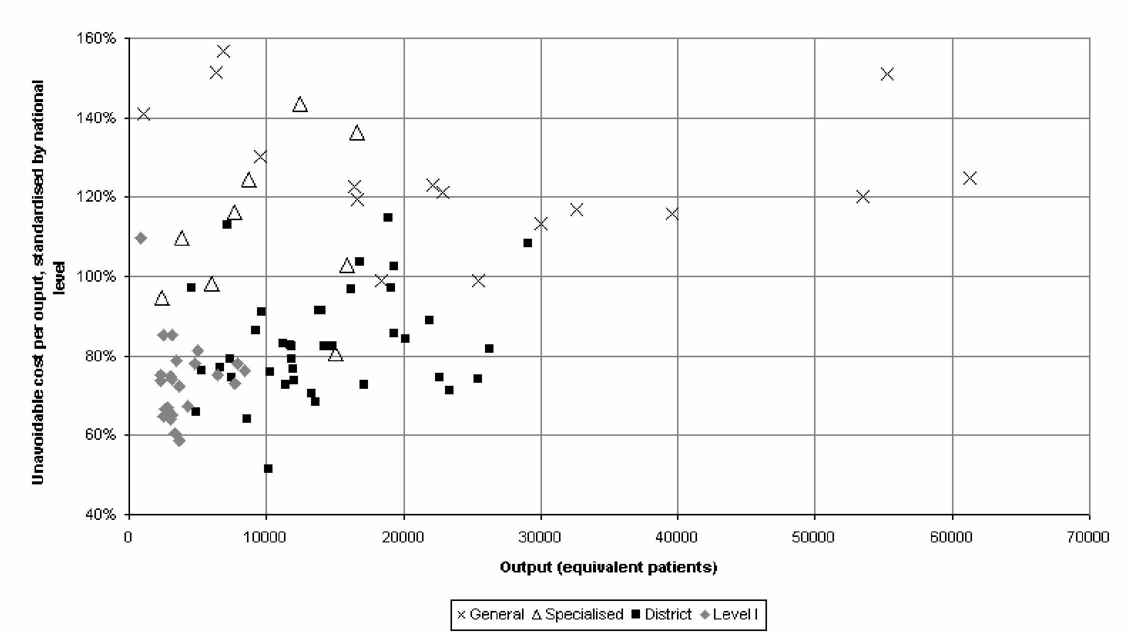


Figure 4: UC indices for MLM model (computed under equation 11)

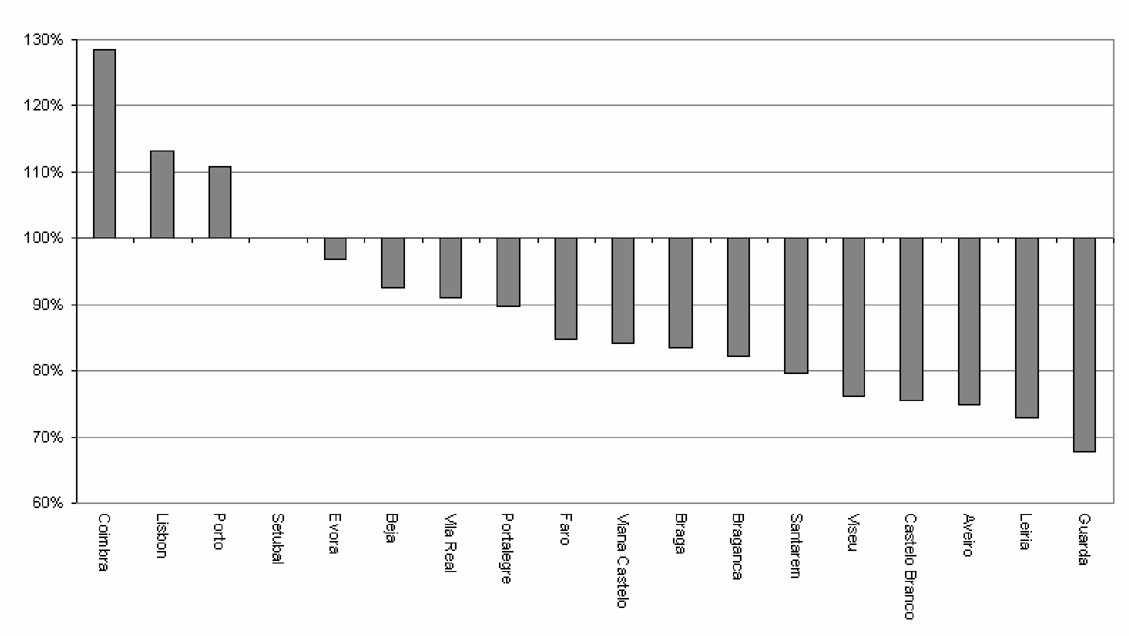
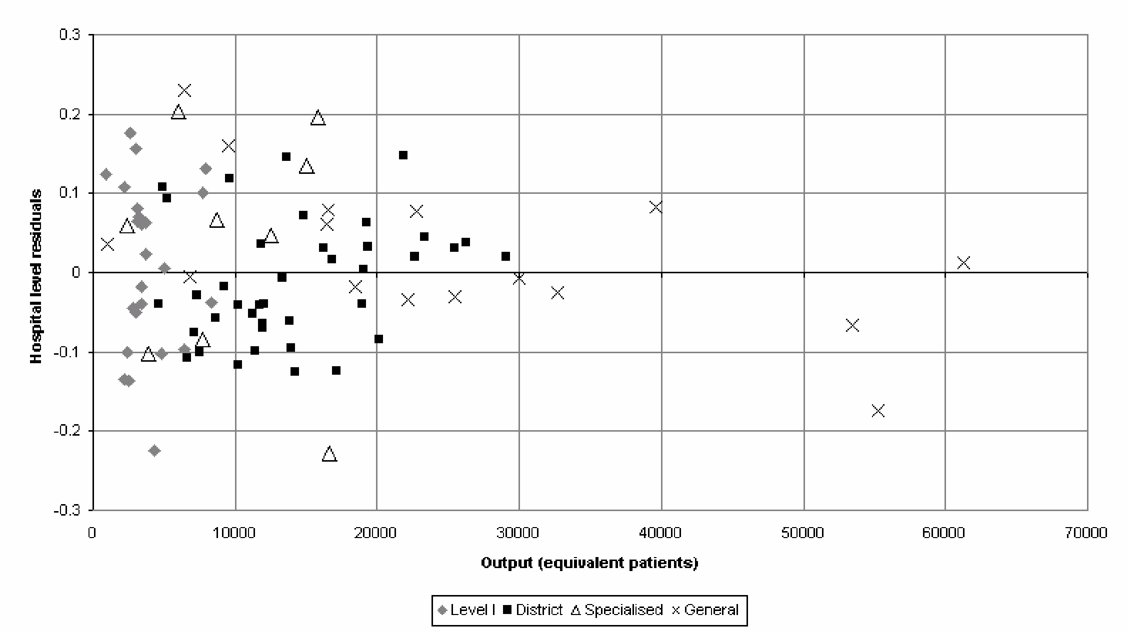


Figure 5: Residuals at the hospital level



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