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Considering Endogeneity, Quality of Care and Casemix- A Hierarchical Random Parameters Approach To Measuring Efficiency For Out of Hours Primary Care Services in Ireland

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Introduction and Background:

Measuring efficiency using parametric methods has been a common theme in the literature in recent years. Stochastic Frontier Analysis (SFA)[1] has been a dominant parametric technique since the seminal papers of Aigner, Lovell & Schmidt (1977) and Meeusen and Van den Broeck (1977). SFA requires two distributional assumptions to be made, the first for the stochastic error component and the second for a one sided error component representing inefficiency. It is also necessary to specify a functional form. The existence of flexible functional forms and distributions, as well as evidence from the SFA literature suggesting that choices of the latter do not greatly affect efficiency results (Hollingsworth and Wildman 2002, Kumbhakar and Lovell 2000) abate concerns about the need to make such choices.

Applying these models to healthcare is more complicated as inherent in healthcare data are immeasurable elements associated with quality of care and patient casemix. This analysis considers a stochastic production frontier (SPF) approach to estimating efficiencies for organisations in the Republic of Ireland (ROI) that supply GP services outside of normal working hours. These organisations are run out of a number of primary care centres. The daily payroll for the centre is the output in the SPF and the services offered by these centres enter the production function as inputs. It is argued that these services are exogenous variables (Lordan, 2006a, Lordan 2006b) and are determined by patient characteristics and reported conditions and not the staff within the centre.

[1] For a complete review of SFA the reader is referred to Kumbhaker and Lovell (2000)

A characteristic of the data used in this study is a two-tier structure emanating from a centre lying within a co-op. Therefore the study includes variables at a co-op and a centre level. To account for this tier structure the analysis considers a random parameters approach previously considered by Craig et al. (2003). In this case three centre level variables are specified as random parameters and are assumed to be affected by two co-op level variables. To model both centre level and co-op level variables as dependant variables would be erroneous as this would ignore the inherent data structure, while to ignore the co-op level variables would be to omit variables that are theoretically justified as part of the model. Therefore it is argued that the random parameters approach is the most appropriate as it allows for the hierarchical data structure.

The analysis also considers proxies for quality of care and casemix in the analysis and incorporates them into the SPF. The sensitivity of efficiency values to the excluding the random parameters, quality of care and casemix variables is examined by estimating three reduced forms of the model which ignore each of these elements. While conclusions in this analysis are specific to the data used, they may prove useful when considering the sensitivity of efficiency values to excluding proxies of intangible elements that feature in a firm's production function. Equally, for any analysis where endogeneity of variables is a concern the solution posed in this paper may be useful in future research.

Sample and Data:

The models for this paper are estimated using data from a 39 co-op centres in the ROI. The data were collected and collated by the author. Co-ops and their centres were set up to provide primary care services outside normal GP working hours. There is a co-op[2] distributed geographically in eight of the former health boards in ROI and each of these co-ops operates independently. Each co-op provides services from one triage unit and a number of centres. These centres have facilities similar to those expected from an in-hours general practitioner (GP) service. The overall structure of these services may be seen as two levels, whereby the co-op contains a number of centres and one triage unit.

The co-op makes all high level management decisions for the centres and delegates funding. The standard service of the co-op is 6pm to 8am on weekdays and 10am to 8am on weekends and public holidays. Some centres open less then these times depending on forecasted demand. The services offered are:

a) A consultation with a GP in one of the co-ops treatment centres

b) A consultation with a GP in the patient's own home

c) Advice via telephone from a center's triage GP

An additional service of triage advice may be provided from the triage unit. The triage advice may be provided by a nurse (nurse triaging) or a doctor (doctor triaging)[3]. When patients place a call to the co-op they are connected to the triage unit, where an operator takes their name and address. A triager then discusses the purpose of the patients' call, their characteristics and their symptoms to establish which service the patient needs. If a

[2] Within the former eastern health board in Ireland exist four co-ops exist; these co-ops are run slightly different to the other health boards' co-ops and contain only one treatment centre. For the purpose of convenience and given that this does not affect our analysis (their data is not used) these four co-ops will be discussed as if they operated as one unit.

[3] In this sample four co-ops have a nurse triage unit and one co-op has a doctor triage unit

patient is to receive triage advice for their complaint it is provided by the triager at this point. For any of the other services the patient is referred to their nearest centre. The individual using this service is tracked from the point of their original contact with the operator through to their final diagnosis and treatment.

The data are a balanced panel for five co-ops in Ireland with N=39 (number of centres) and T=365 (number of days) for the period 01 May 2004 to 01 May 2005. The dependant variable (output) is payroll and is calculated based on the quantity of nursing, medical and administrative staff employed daily by the centre multiplied by their price of labor[4]. Three inputs are considered: quantity of home visits, quantity of treatment centre consultations, and quantity of doctor advice for each day.

Additional variables are included in the model to account for patient casemix, quality of care of the centre and the co-op hierarchy. A clinical indicator which has been dubbed 'priority' indicates how serious the caller's complaint is. When a caller rings a qualified nurse places a marker on the individuals name indicating whether this caller is considered a priority or not. These indicators are aggregated to provide an estimate of the number of high priority cases daily. A second indicator considered is the quantity of calls received between 12am and 8am (red eye). It is argued that individuals would only ring during these late hours for urgent matters. Again, this indicator is aggregated to represent the number of 'redeye' calls received.

[4] For administrative, driving and nursing staff this is straightforward as these staff are paid hourly. For medical staff, locum staff are paid hourly whereas GP's are paid a fee for the quantity of home visits and treatment centre visits that they provide. This fee differs for public and private patients.

Three reaction time variables are constructed to capture how fast the joint effort of the triage unit and the centre is to a patient's call. Relating to the doctor advice service the first reaction variable is defined as the difference between the time the person rang and the time they received medical advise. Relating to home and treatment centre visits, two variables are constructed and are defined as the difference between the time the person rang and the time they received their direct consultation with a GP.

Two additional co-op level variables are included relating to the co-ops' triage units. The first is the quantity of triage advice distributed daily and the second relates to the triage units daily payroll. The latter is calculated based on the quantity of nursing, medical and administrative staff employed multiplied by their price of labor[5]. A fixed coefficient[6] is also included in the variable set to indicate which co-op a centre belongs to. Descriptive statistics of these variables are documented in table 1:

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Payroll	1130.54	1130.6	.0000	10115
Priority	2.53	3.65	.0000	48
Triage advise	52.57	47.27	.0000	298
Home Visits	3.76	2.98	.0000	29
Treatment Centre Visits	14.36	16.41	.0000	191
Doctor Advice	4.53	7.72	.0000	160
Redeye	2.07	2.80	.0000	25
Triage Unit Total Pay	2492.90	2218.375	587.52	9543
Home Visit Reaction Time	157.61	234.623098	.0000	5176
Treatment Centre Reaction Time	859.0795	1465.79649	.0000	28116
Doctor Advise Reaction Time	86.5915	265.901392	.0000	13180

[5] For administrative and nursing staff this is straightforward as these staff are paid hourly. For medical staff, locum staff is paid hourly whereas GP's are paid a fee for the quantity of home visits and treatment centre visits that they provide. This fee differs for public and private patients.
[6] One of these dummies in naturally excluded in the estimation of the heterogeneity model in order to continue to include the constant term

Stochastic Production Frontier:

The traditional stochastic production frontier model (Aigner, Lovell & Schmidt (1977), Meeusen and Van den Broeck (1977)) can be represented by:

$$y_i = \alpha + \beta' x_i + v_i - u_i \tag{1}$$

where y_i is the amount produced by the i^{th} firm, x_i is a K * 1 vector of inputs and B is an unknown parameter vector to be estimated. Notably the error term has two components; the first is $v_i \sim N[0, \sigma_v^2]$ and is equivalent to the traditional stochastic error. The second is a one-sided error component u_i that allows a firm to lie away from the best practice frontier. In the seminal papers $u_i \sim N[0, \sigma_u^2]$ and both v_i and u_i are assumed to be uncorrelated. Alternatively u_i may follow an exponential, truncated normal (Stevenson (1980) or gamma (Greene (1980, 1990).

A firms' efficiency is calculated based on actual output produced divided by the level of output that would have ensued technical inefficiency was zero. Equation 1 illustrates a stochastic production frontier for panel data with time invariant inefficiencies, this assumption is relaxed when random parameters are introduced into the model. The conditional distribution of u_i given e_i can be used estimate u_i for the normal-half normal stochastic production frontier[7] as originally proposed by Jondrow et al. (1982):

$$E[u_i \mid e_i] = \sigma_* [\frac{\phi(e_i \kappa / \sigma)}{1 - \Phi(-e_i k / \sigma)} + (e_i k / \sigma)$$

[7] Conditional estimators for the normal-exponential, normal-gamma models may be found in the quoted seminal papers.

$$E[u_i \mid e_i] = [\frac{\sigma\lambda}{1+\lambda^2}][\tilde{\mu}_{it} + \frac{\phi(\tilde{u}_{it})}{\Phi(\tilde{u}_{it})}]$$

where

$$\varepsilon_i = y_i - B^{'} x_i = v_i - u_i$$

$$\tilde{\mu}_i = -\lambda\varepsilon_{it} / \sigma$$

$$\sigma = [\sigma_u^2 + \sigma_v^2]^{.5}$$

$$\lambda = \sigma_u / \sigma_v$$

Given $E[u_i \mid e_i]$ a firms' efficiency can be calculated as $TE_i = \exp(-u_i)$. Values for efficiency are between zero and one, a firm with a technical efficiency of one being fully efficient. The difference between 1 and the actual efficiency value obtained 'provides a measure of the shortfall of observed output from maximum feasible output' (Kumbhaker and Lovell 2000).

Methodology:

Before the framework described in equation 1 can be applied to the data it is necessary to decide on an appropriate measure for output. The natural choice in the healthcare literature may be to consider a measure of the service offered to patients, such as beds in the case of hospitals or the quantity of surgery visits in the case of measuring GP efficiency. This poses a problem in the current setting as the co-op's centres offer three very different types of services; treatment centre visits, home visits, and doctor advice. A solution would be to consider a dual approach which involves estimation of a cost or profit function, and requires price data. It also assumes cost minimization or profit maximization behavior. It is questionable if such assumptions are justified for health services, but this question is moot given that full price data are unavailable.

Alternatively, if a suitable aggregated measure exists it can be used to create a dependent variable for SFA. Initially an obvious choice is to consider the price of the service as an appropriate weight in which to aggregate services. However in the case of co-op centres doctor advise is free of charge and this does not reflect its value to the patient receiving it. Also, in ROI there are two different groups of patients who attend the co-ops, private and public, and these groups pay different charges[8] for the treatment centre and home visit services. Again, these discriminating prices do not fully reflect the value of these patients.

Ignoring the latter problems and assuming it is justified to aggregate services using price of service, to enforce the framework of equation one it is necessary to specify inputs. A natural choice for inputs is labour data, which is quantity of nurses, administration staff, medical staff and drivers employed by the co-op weighted by the price of labour. It follows we assume the latter are exogenous. This may not be a plausible assumption, the service itself is an emergency out of hours, and therefore the quantity of staff on a rota is a function of the quantity of calls received and the type of services provided daily and not vice versa. Therefore staffing levels are not theoretically exogenous to the equation.

This analysis considers an original approach where payroll is considered as an output in the health production function and services offered by the healthcare facility are seen as inputs. That is, in this case we postulate that the services offered to the patient are exogenous. The latter is true if and only if services offered to the patient are not determined by the co-op staff but are driven by factors outside the co-ops' control. In this

[8] A public patient in ROI does not pay for these services, whereas a private patient pays the fees as determined by the co-op.

instance, we argue that services are driven by the condition the patient reports when they first contact the co-op, their age, severity and possibly their sex.

Lordan (2006a) explores the latter by considering gastroenteritis patients that present to the co-op. This illness category is chosen as it covers a wide range of symptoms, can potentially affect all individuals in the population and its severity varies considerably with patient characteristics. Therefore it is expected that the services offered to the patient will also vary. The author considers a discrete choice approach when considering the factors that determine the service the patient receives. A multinomial logit is employed which allows for patient, call and co-op characteristics to affect the choice variable. The results indicate that patient and call characteristics are the elements that ultimately affect the service the patient receives and find co-op characteristics to be insignificant in this choice. Lordan (2006b) extends the latter analysis by considering a number of disease classes. The results again show that co-op characteristics are jointly insignificant in determining service choice.

Accepting the hypothesis that services are not determined by the co-op staff but are driven by exogenous factors we may extend equation 1 to allow for panel data and consider one modification:

$$y_{ict} = \alpha + \beta' x_{ict} + v_{ict} + u_{ic} \qquad (2)$$

In this case y_{ict} represents the payroll of i^{th} centre in the c^{th} co-op for day t, x_{ict} is a K * 1 vector of inputs corresponding to the quantity of treatment centre visits, the quantity of home visits and the quantity of doctor advise dispensed by a centre i in co-op c for day t. β is an unknown parameter vector to be estimated, $v_{ict} \sim N[0,\sigma_v^2]$ and $u_{ic} \sim N[0,\sigma_u^2]$.

In order to produce credible efficiency estimates from healthcare data it is necessary to look at incorporating both casemix and quality of care. In addition, unique to this data set is a hierarchical structure whereby every centre is encompassed within a co-op. For these reasons a model with a cobb-douglas[9] functional form and the following parameters is considered:

$$Lnp_{ict} = \alpha_i + \beta_1 m_1 + \beta_2 m_2 + \beta_3 m_3 + \beta_4 m_4 + \beta_5 \ln y_{1ict} + \beta_6 \ln y_{2ict} + \beta_7 \ln y_{3ict}$$
$$+ \beta_8 \ln z_{1ict} + \beta_{92} \ln z_{2ict} + \beta_{10} \ln z_{3ict} + v_{ict} - u_{ict} \quad (3)$$

Where:

$v_{ict} \sim N[0,\sigma_v^2]$

$u_{ict} \sim N[0,\sigma_u^2]$

$$\alpha_i = \alpha_0 + \alpha_1 \ln x_{1_i c} + \alpha_2 \ln x_{2ic} + \alpha_3 \ln h_{1c} + \alpha_4 h_{2c} + u_{\alpha i} \quad (4)$$

$$\beta_5 = \chi_0 + \chi_1 \ln x_{1ic} + \chi_2 \ln x_{2ic} + \chi_3 \ln h_{1c} + \chi_4 h_{2c} + u_{\chi i} \quad (5)$$

$$\beta_6 = \psi_0 + \psi_1 \ln x_{1ic} + \psi_2 \ln x_{2ic} + \psi_3 \ln h_{1c} + \psi_4 h_{2c} + u_{\psi i} \quad (6)$$

$$\beta_7 = \phi_0 + \phi_1 \ln x_{1ic} + \phi_2 \ln x_{2ic} + \phi_3 \ln h_{1c} + \phi_4 h_{2c} + u_{\phi i} \quad (7)$$

where "*i*" denotes centre 1…39 and "*c*" denotes co-op 1….5. In equation 3 p is equal to total payroll for centre i in co-op c for time t. The primary inputs y_1, y_2 and y_3 are equal to

[9] The most common function forms in the stochastic frontier literature are cobb-douglas, translog and reduced translog. Cobb-Douglas was chosen for this analysis as the more flexible alternatives yielded marginal gains in terms of log-liklehood

the quantity of home visits supplied daily, the quantity of doctor advice given daily and the quantity of treatment centre visits daily respectively.

The dummy variables $m_1 \ldots m_4$[10] and z_1,z_2,z_3 are included as measures of quality of care. The former indicates the co-op in which the centre belongs. The co-op makes managerial decisions for the centres such as funding allocation, opening hours etc. and therefore it follows that such decisions will impact quality of care distributed at centre level. This is specified as a fixed effect. Given that the data are over a period of one year it is postulated that decisions made at co-op level will have a constant effect on quality of care over the sample. The latter, z_1,z_2,z_3, correspond to the reaction time in minutes it takes to provide the services of a home visits, doctor advise and treatment centre aggregated to a daily measure. At a micro level it is measured as the time elapsed between a patient contacting the triage centre and receiving one of the latter services. Reasonably a centre that has the lowest reaction time is the least wasteful and the most efficient *cetrius paribus*.

Four random parameters are included in the model, α, y_1, y_2, y_3 and are specified by equations 4, 5, 6 and 7. The four random parameters are assumed to be affected by two sets of variables. x_1, x_2 are time invariant casemix variables for the centre. Specifically x_1 represents the number of cases seen in the redeye by the centre over the sample. It is argued that individuals will only contact an out of hours service in these late hours if they

[10] Dummy m_5 has been dropped to avoid multicollinearity.

self diagnosis themselves as severe. x_2 is defined by clinical staff as the quantity of emergency and urgent cases seen by the centre in the sample year. It is postulated that both these variables can affect the quantity of y_1, y_2, y_3 assuming that a centre that treats more severe cases *ceterius paribus* will spend longer with these patients and this will affect the quantity of services. It follows that these casemix variables will also affect the random effect α. The second set of variables included are co-op specific and are included to account for the data hierarchy attributed to the two-level data structure. h_{1c} relates to the number of advise calls dispensed by the co-ops triage centre in the sample year, it follows that the more calls the triage centre deals with the less quantity of y_1, y_2, y_3 will be required *cetrius paribus*... h_{2c} relates to the annual triage centre payroll. Its affect on the quantity of y_1, y_2, y_3 is ambiguous, if the triage centre has a high payroll the quantity of y_1, y_2, y_3 may be negatively effected if the extra resources are transferred into increased nurse advise, equally the extra resources may result in more calls been taken and therefore an increased need for treatment centre visits, doctor advise and home visits. Again both h_1 and h_2 are allowed affect α. It is argued that allowing these variables to affect y_1, y_2, y_3 will reflect the relationship between the centres and their respective co-ops by allowing activities at co-op level to impact centre activities appropriately.

$u_{\alpha i}, u_{Bi,} u_{\psi_i} u_{\phi i}$ are the stochastic elements of the random parameters and are normally distributed with zero mean and constant variance.

Equation 3 can be estimated by simulated maximum likelihood methods (Greene 2001, Train 2002) and follows an approach utilised by Craig *et al.* (2003). In the latter study the authors employ a hierarchical linear random parameters model to assess the impact of cultural factors on box office receipts for US films in foreign markets. The authors also allow for film-specific heterogeneity. While the random parameters (Greene 2001, 2004a) formulation has yet to be used to allow for a multi level structure in stochastic frontier analysis, it originated from the need to control for time invariant heterogeneity and in this context it has been employed to SFA, for example Greene (2004a,2004b) utilized the random parameters model to control for country specific heterogeneity when examining a 191 country 5 year panel of World Health Organization data relating to health care delivery. Hajargast (2004) consider a model in which the constant term is the only random parameter ('true' random effects specification (Greene 2001, 2004a) and extend it to its semi-parametric counterpart.

Results from three reduced forms of the model outlined are also reported, namely a model that ignores quality of care, a model that ignores casemix and a model that ignores the random parameters structure. In the case of the latter reduced form model both casemix and the two-tier structure are ignored and all variables are non-random, therefore we expect this model to have the most severe changes in efficiency when compared to the full model. This model reduces to a random effects model (Pitt and Lee (1981)) for panel data with time invariant inefficiencies.

Considering three alternate specifications allows comparisons to be made on the affect of such exclusions on efficiency values, their averages and standard deviations, their kernel densities and their rankings. Specifically the affect of ignoring quality of care variables will have an ambiguous affect on the firms individual efficiency results but should widen their spread overall. For a firm who displays excellent quality of care, if their efforts are unaccounted for we expect this to cause a downward bias in their individual efficiency. For a firm whose quality of care is poor, ignoring their lack of effort will bias their individual efficiencies upwards. The overall result is expected to be wider efficiency bands *a priori*. The *a priori* expectation of ignoring casemix is downward biased individual efficiencies. This is attributed to dubbing the increased resources needed to treat severe casemix as wasteful. The change to the shape and the spread of the overall efficiencies is limited to the diversity of casemix that exists across centres.

It is predicted that ignoring the random parameters formulation will have the most severe effect on efficiencies, their spread and their shape. The effects of ignoring the casemix component of the random parameters are as specified above. Ignoring the co-op variables component of the random parameters excludes the hierarchical nature of the data and ignores the impact that these variables have on the variables y_1, y_2, y_3. It is not known *a priori* whether the effect these variables have on these quantities is overall positive or negative, what is known is that these variables should theoretically be included in the model. The predicted affect on the efficiencies is that the time invariant heterogeneity will be subsumed into the predictions from which the efficiencies are drawn. This will distort efficiency results and any inference that is based on them. The extent to which the shape and spread of the kernel densities associated with these results is affected is dependant on the level of the time invariant heterogeneity that exists across centres. The following outlines these three models and all variable definitions are consistent with equation 3.

Ignoring Quality of Care:

$$Lnp_{ict} = \alpha_i + \beta_1 \ln y_{1ict} + \beta_2 \ln y_{2ict} + \beta_3 \ln y_{3ict} + v_{ict} - u_{ict} \quad (7)$$

Where:

$v_i \sim N[0, \sigma_v^2]$

$u_i \sim N[0, \sigma_{ut}^2]$

$\alpha_i = \alpha_0 + \alpha_1 \ln x_{1ic} + \alpha_2 \ln x_{2ic} + \alpha_3 \ln h_{1c} + \alpha_4 h_{2c} + u_{\alpha i}$

$B_1 = \chi_0 + \chi_1 \ln x_{1ic} + \chi_2 \ln x_{2ic} + \chi_3 \ln h_{1c} + \chi_4 h_{2c} + u_{Bi}$

$\beta_2 = \psi_0 + \psi_1 \ln x_{1ic} + \psi_2 \ln x_{2ic} + \psi_3 \ln h_{1ic} + \psi_4 h_{2ic} + u_{\psi i}$

$\beta_3 = \phi_0 + \phi_1 \ln x_{1ic} + \phi_2 \ln x_{2ic} + \phi_3 \ln h_{1ic} + \phi_4 h_{2ic} + u_{\phi i}$

Ignoring Casemix:

$$Lnp_{ict} = \alpha_i + \beta_1 m_1 + \beta_2 m_2 + \beta_3 m_3 + \beta_4 m_4 + \beta_5 \ln y_{1ict} + \beta_6 \ln y_{2ict} + \beta_7 \ln y_{3ict}$$
$$+ \beta_8 \ln z_{1ict} + \beta_9 \ln z_{2ict} + \beta_{10} \ln z_{3ict} + v_{ict} - u_{ict} \quad (8)$$

Where:

$$v_i \sim N[0, \sigma_v^2]$$

$$u_i \sim N[0, \sigma_{ut}^2]$$

$$\alpha_i = \alpha_0 + \alpha_1 \ln h_{1c} + \alpha_2 h_{2c} + u_{\alpha i}$$

$$B_5 = \chi_0 + \chi_1 \ln h_{1c} + \chi_2 h_{2c} + u_{Bi}$$

$$\beta_6 = \psi_0 + \psi_1 \ln h_{1c} + \psi_2 h_{2c} + u_{\psi i}$$

$$\beta_7 = \phi_0 + \phi_1 \ln h_{1c} + \phi_2 h_{2c} + u_{\phi i}$$

Ignoring Random Parameters:

$$Lnp_{ict} = \alpha + \beta_1 m_1 + \beta_2 m_2 + \beta_3 m_3 + \beta_4 m_4 + \beta_5 \ln y_{1ict} + \beta_6 \ln y_{2ict} + \beta_7 \ln y_{3ict}$$
$$+ \beta_8 \ln z_{1ict} + \beta_9 \ln z_{2ict} + \beta_{10} \ln z_{3ict} + v_{ict} - u_{ic} \qquad (9)$$

Where:

$$v_i \sim N[0, \sigma_v^2]$$

$$u_i \sim N[0, \sigma_u^2]$$

Results:

The first three models considered in this study are estimated by simulated maximum likelihood using 1000 Halton draws. The fourth model is estimated by maximum likelihood. All models are estimated using Limdep (Greene 2002). +1 was added to every variable in the dataset to eliminate zero values[11] for creating natural logs. The parameter estimates from the empirical analysis are documented in table 2a and 2b.

[11] Sensitivity testing was carried out by adding +2, +3, +4, +5, +10, +20, +40, +100 with robust results. The models were less robust when small fractions were added to the variables, .00001, .000001, .0000001. This is due to the large negative log values of the latter fractions.

To chose between the models it is useful to consider both theoretical and statistical groundings. From a theoretical viewpoint it is expected model 1 is more appropriate and excluding elements of casemix, quality of care and the tier structure can potentially distort efficiency estimates and rankings. From a statistical standpoint, the aim of this type of modeling is to estimate accurate efficiency estimates and these elements may have no impact on such estimates. For these non-nested models AIC, BIC and AIC_c statistics are reported to allow some inference to be made regarding the most appropriate model.

The parameters are relatively consistent with the direction expected *a priori*. Examining σ_u and λ, model 1 clearly has the smallest values. This indicates that some variation is being moved from the inefficiency values with the addition of casemix and quality of care variables. It indicates the same for the random parameters. A visual inspection of the log-likehoods shows a large difference between the likelihood attached to model 1 and model 4. This suggests that ignoring the two-level structure has a significant effect on the models fit. Visually inspecting the log-likelihoods of model 1, model 2 and model 3 there is a more modest gain for model 1. Comparing the four non-nested models using AIC, BIC and AIC_c criteria model 1 is again favored; the biggest difference again is model 4 with marginal gains seen between model 1, 2 and 3.

Table 2a: Parameter Estimates

	Model 1			**Model 2**			
Parameters	Estimate	Std Error	Prob	Estimate		Std Error	Prob
Non-Random Parameters							
$Ln(m_1)$	.47016514	.00695450	.0000	N\A		N\A	N\A
$Ln(m_2)$	.09895504	.01660158	.0000	N\A		N\A	N\A
$Ln(m_3)$	-.52589976	.00750736	.0000	N\A		N\A	N\A
$Ln(m_4)$	.29800316	.00742361	.0000	N\A		N\A	N\A
$Ln(z_1)$	.02596073	.00169082	.0000	N\A		N\A	N\A
$Ln(z_2)$	.00775797	.00173189	.0000	N\A		N\A	N\A
$Ln(z_3)$	.05883666	.00145878	.0000	N\A		N\A	N\A
Random Parameters							
			Constant				
Intercept	2.73918858	.03721329	.0000	2.36885774		.03669887	.0000
$Ln(x_1)$	.12696657	.00295217	.0000	.23748238		.00250716	.0000
$Ln(x_2)$	.19383383	.00535698	.0000	.24477977		.00542205	.0000
$Ln(h_1)$	.27621732	.00644805	.0000	.27332426		.00677065	.0000
$Ln(h_2)$	.06870206	.00544659	.0000	.08456316		.00575355	.0000
Std. Dev.	.53232540	.00185072	.0000	.46979725		.00224994	.0000
			y_1				
Intercept	.08134260	.03396115	.0166	.03005657		.03319896	.3653
$Ln(x_1)$	-.00290447	.00373322	.4366	-.01829073		.00361092	.0000
$Ln(x_2)$	-.00061826	.00531878	.9075	.02015967		.00494554	.0000
$Ln(h_1)$	-.02278818	.00478311	.0000	-.02773857		.00518830	.0000
$Ln(h_2)$	.00511467	.00473938	.2805	-.00853257		.00511145	.0951
Std. Dev.	.01439671	.00173765	.0000	.04588454		.00196177	.0000
			y_2				
Intercept	1.18464859	.02394831	.0000	1.35276189		.02453521	.0000
$Ln(x_1)$	-.11384054	.00222826	.0000	-.08308922		.00208931	.0000
$Ln(x_2)$	-.02671557	.00362238	.0000	-.05303594		.00359507	.0000
$Ln(h_1)$	-.03692218	.00324376	.0000	-.04607980		.00349951	.0000
$Ln(h_2)$	.03490614	.00312177	.0000	.01936508		.00335715	.0000
Std.Dev.	.02358379	.00097054	.0000	.02993881		.00109486	.0000
			y_3				
Intercept	.43631682	.04278695	.0000	.63764681		.04642376	.0000
$Ln(x_1)$	-.00758946	.00412882	.0660	-.00268244		.00415607	.5186
$Ln(x_2)$	-.02093292	.00660168	.0015	-.03928947		.00703362	.0000
$Ln(h_1)$	-.01228065	.00538657	.0226	-.02612397		.00589808	.0000
$Ln(h_2)$	-.04206711	.00538511	.0000	-.04842123		.00595303	.0000
Std. Dev.	.00565969	.00178504	.0015	.00105206		.00203827	.6057
Parameters of Two Part Error Component							
σ	.57446	.00210632	.0000	.79792775		.00192893	.0000
λ	2.4301	.02369146	.0000	3.7380		.02490561	.0000
σ_u	.52777			.77082			
σ_v	.21740			.20621			
Log Liklehood							
Log Liklhood	-1085	BIC	2563	Log Liklehood	-1245	BIC	2845
AIC	2252	AIC_c	2252	AIC	2564	AIC_c	2564

Table 2b: Parameter Estimates

	Model 3			Model 4		
Parameters	Estimate	Std Error	Prob	Estimate	Std Error	Prob
Non-Random Parameters						
Constant	N\A	N\A	N\A	5.14842283	.01922892	.0000
Ln(m_1)	.39586349	.00745617	.0000	.52389952	.01812745	.0000
Ln(m_2)	.32429941	.01568243	.0000	.24951704	.03870076	.0000
Ln(m_3)	-.23611279	.00822578	.0000	.34313136	.02104822	.0000
Ln(m_4)	.33065331	.00790082	.0000	.38028461	.02148934	.0000
Ln(z_1)	.03337238	.00168726	.0000	.07736004	.01356897	.0000
Ln(z_2)	.01281851	.00175467	.0000	.55007968	.00835538	.0000
Ln(z_3)	.06044649	.00144677	.0000	.18874820	.01345683	.0000
Ln(y_1)	N\A	N\A	N\A	.04302017	.00381291	.0000
Ln(y_2)	N\A	N\A	N\A	-.00088550	.00420181	.8331
Ln(y_3)	N\A	N\A	N\A	.03383988	.00337886	.0000
Random Parameters						
Constant						
Intercept	2.55127029	.03796419	.0000	N\A	N\A	N\A
Ln(x_1)	.16650577	.00290898	.0000	N\A	N\A	N\A
Ln(x_2)	.22829805	.00541844	.0000	N\A	N\A	N\A
Ln(h_1)	N\A	N\A	N\A	N\A	N\A	N\A
Ln(h_2)	N\A	N\A	N\A	N\A	N\A	N\A
Std. Dev.	.48310427	.00225641	.0000	N\A	N\A	N\A
y_1						
Intercept	.04256208	.03528956	.2278	N\A	N\A	N\A
Ln(x_1)	-.01212085	.00378356	.0014	N\A	N\A	N\A
Ln(x_2)	.00789954	.00545780	.1478	N\A	N\A	N\A
Ln(h_1)	N\A	N\A	N\A	N\A	N\A	N\A
Ln(h_2)	N\A	N\A	N\A	N\A	N\A	N\A
Std. Dev.	.04757035	.00191540	.0000	N\A	N\A	N\A
y_2						
Intercept	1.12890413	.02371527	.0000	N\A	N\A	N\A
Ln(x_1)	-.11407604	.00223909	.0000	N\A	N\A	N\A
Ln(x_2)	-.02064469	.00361331	.0000	N\A	N\A	N\A
Ln(h_1)	N\A	N\A	N\A	N\A	N\A	N\A
Ln(h_2)	N\A	N\A	N\A	N\A	N\A	N\A
Std. Dev.	.02853432	.00105505	.0000	N\A	N\A	N\A
y_3						
Intercept	.44418634	.04298463	.0000	N\A	N\A	N\A
Ln(x_1)	-.01718547	.00422522	.0000	N\A	N\A	N\A
Ln(x_2)	-.02429693	.00664023	.0003	N\A	N\A	N\A
Ln(h_1)	N\A	N\A	N\A	N\A	N\A	N\A
Ln(h_2)	N\A	N\A	N\A	N\A	N\A	N\A
Std. Dev.	.00059232	.00194720	.7610	N\A	N\A	N\A
Parameters of Two Part Error Component						
σ	.75068061	.00227565	.0000	1.95959	.00476541	.0000
λ	3.35515	.02644537	.0000	4.85	.06145385	.0000
σ_u	.71941			1.91846		
σ_v	.21442			.39552		

Log Liklihood							
Log-Lik	-1427	BIC	3048	Log- Lik	-8617	BIC	17349
AIC	2902	AIC_c	2902	AIC	17258	AIC_c	17258

The primary focus of this analysis is gauging the differences in the efficiency values resultant from the four models. Models 1, 2 and 3s output includes time variant efficiency values. Model 4's (the random effects model common to the literature) output includes time invariant inefficiency values. For comparison purposes the efficiency values from the former three models are averaged to produce a centre specific efficiency value comparable to model 4. The descriptive statistics associated with these values are published in table three.

Table 3: Descriptive Statistics for Efficiency Values:

	Mean	Std. Dev.	Min	Max
Model 1	.664433670	.045441078	.445124014	.743105106
Model 2	.598648057	.104935696	.0632301063	.751894026
Model3	.538901592	.120354092	.0180727479	.725802361
Model 4	.351125790	.134202297	.0434076033	.610749497

The highest mean and the lowest standard deviation are associated with the broadest model. Model 2, 3, and 4's minimum values are very extreme when compared to model 1's minimum. While this does not give us a clear picture of the effect of broadening the model on the efficiency values, it is an indication that including casemix, quality of care and a hierarchical structure moves variation that was initially dubbed as 'inefficiency' out of the one-sided error term. The result is higher and more narrow ranged efficiency values.

Table 4 documents the average efficiency and rankings for each centre; on visual inspection it seems estimates were indeed very sensitive to the exclusion of quality of care, casemix and the two-level hierarchy respectively as predicted.

Table 4: Efficiency Values and Rankings:

Centre No.	Model 1	Rank	Model 2	Rank	Model 3	Rank	Model 4	Rank
1	0.7101	6	0.7240	2	0.7258	1	0.1310	38
2	0.6241	38	0.5125	37	0.4974	28	0.2250	32
3	0.6392	36	0.5633	32	0.5672	18	0.3458	20
4	0.6398	35	0.5628	33	0.5591	19	0.2422	31
5	0.6581	25	0.6167	17	0.6352	7	0.4448	11
6	0.6639	16	0.6281	12	0.6489	6	0.3966	15
7	0.6743	13	0.6551	10	0.6792	4	0.4980	8
8	0.6468	31	0.5835	25	0.5806	15	0.3103	23
9	0.6447	33	0.5781	28	0.5779	17	0.2861	26
10	0.6443	34	0.5754	29	0.5786	16	0.3247	22
11	0.6619	18	0.5801	27	0.5234	25	0.3311	21
12	0.7151	5	0.7051	3	0.6763	5	0.1507	37
13	0.6384	37	0.5080	38	0.4547	34	0.2204	33
14	0.6624	17	0.5820	26	0.5265	24	0.2424	30
15	0.6510	28	0.5494	35	0.4956	29	0.2862	25
16	0.6835	11	0.6553	9	0.6856	2	0.5047	6
17	0.6590	21	0.5742	30	0.5085	26	0.2705	29
18	0.7172	4	0.7041	5	0.6130	9	0.3836	17
19	0.4451	39	0.0632	39	0.0181	39	0.0434	39
20	0.7431	1	0.7519	1	0.6854	3	0.3539	19
21	0.7189	2	0.7044	4	0.6194	8	0.4195	13
22	0.7177	3	0.7018	6	0.6109	10	0.4278	12
23	0.7014	8	0.6281	13	0.5892	14	0.5067	5
24	0.6918	9	0.6069	18	0.5524	20	0.6058	2
25	0.6910	10	0.5960	19	0.5369	22	0.6107	1
26	0.7027	7	0.6349	11	0.5928	13	0.5175	4
27	0.6586	23	0.5916	22	0.4611	31	0.3726	18
28	0.6450	32	0.5411	36	0.3880	38	0.5258	3
29	0.6492	30	0.5571	34	0.4060	37	0.2865	24
30	0.6496	29	0.5656	31	0.4117	36	0.2749	28
31	0.6590	22	0.5952	21	0.4641	30	0.4108	14
32	0.6616	19	0.6209	14	0.5454	21	0.1853	36
33	0.6607	20	0.6176	16	0.5353	23	0.2009	35
34	0.6762	12	0.6653	7	0.6019	12	0.2178	34
35	0.6648	15	0.6201	15	0.5045	27	0.4978	9
36	0.6720	14	0.6555	8	0.6042	11	0.2857	27
37	0.6565	26	0.5902	23	0.4588	32	0.3939	16
38	0.6582	24	0.5959	20	0.4548	33	0.4579	10
39	0.6559	27	0.5862	24	0.4428	35	0.5045	7

Table 5a and 5b document the correlations and spearman rank correlations associated with the estimates in Table 4.

Table 5a: Efficiency Correlations:

Efficiency Variable	Model 1	Model 2	Model 3	Model 4
Model 1	1.00000	.96442	.83325	.41933
Model 2	.96442	1.0000	.88966	.33597
Model3	.83325	.88966	1.0000	.22512
Model 4	.41933	.33597	.22512	1.000

Table 5b: Spearman Rank Correlations:

Efficiency Variable	Model 1	Model 2	Model 3	Model 4
Model 1	1.00000	0.908502024	0.663967611	0.308097166
Model 2	0.908502024	1.00000	0.789271255	0.203643725
Model3	0.663967611	0.789271255	1.00000	0.078340081
Model 4	0.308097166	0.203643725	0.078340081	1.00000

From 5a the correlations between model 1, 2 and 3 can be described as strong. Model 4, which ignores all random parameters, clearly stands out as producing different efficiency values to the other models. Table 5b documents Spearman rank correlations. This table exhibits lower correlations than table 5a as expected. A very strong correlation still exists between model 1 and model 2 suggesting that ignoring the quality of care variables should not displace a firms place in the rankings too much. The correlation between model 1 and 3 is moderate suggesting that ignoring casemix factors can give misleading efficiency values and greatly displace their rankings. Model 4 stands out as very weakly correlated with the other three models, these results indicate that we are looking at two very different distributions of the one sided error. To examine the differences in shape and placement of the efficiency values it is convenient to examine the kernel densities.

Figure 1a: Kernel Density Estimate for Model 1 Efficiency Values

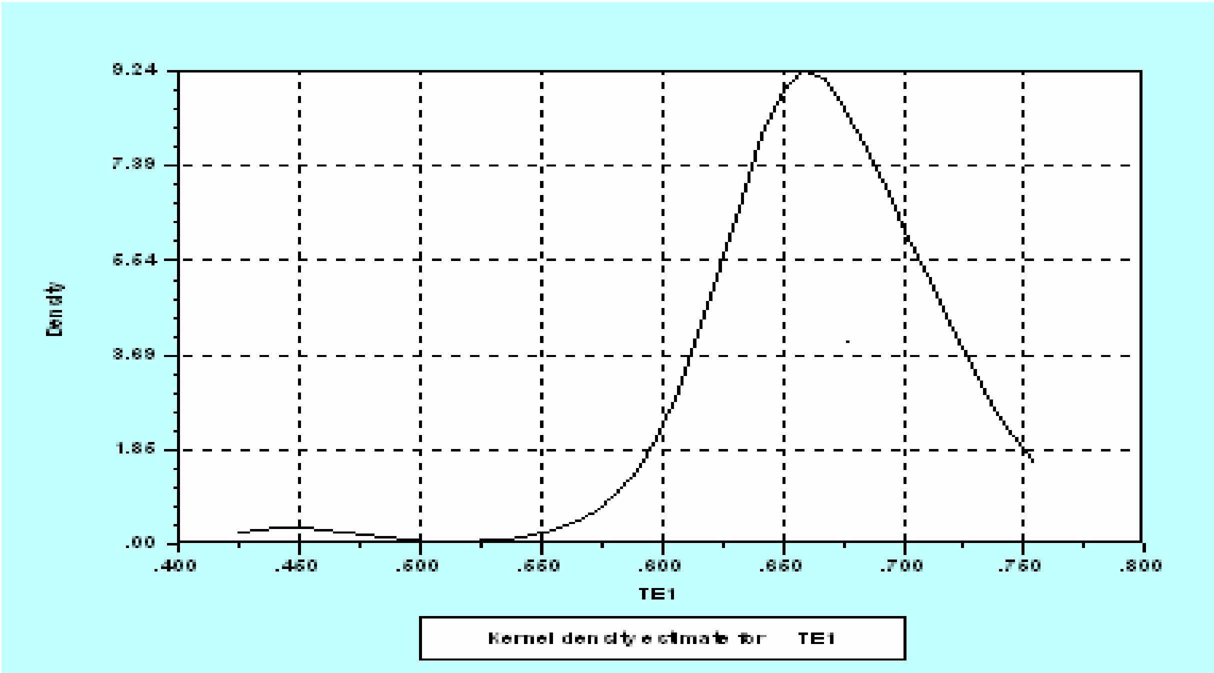


Figure 1b: Kernel Density Estimate for Model 2 Efficiency Values

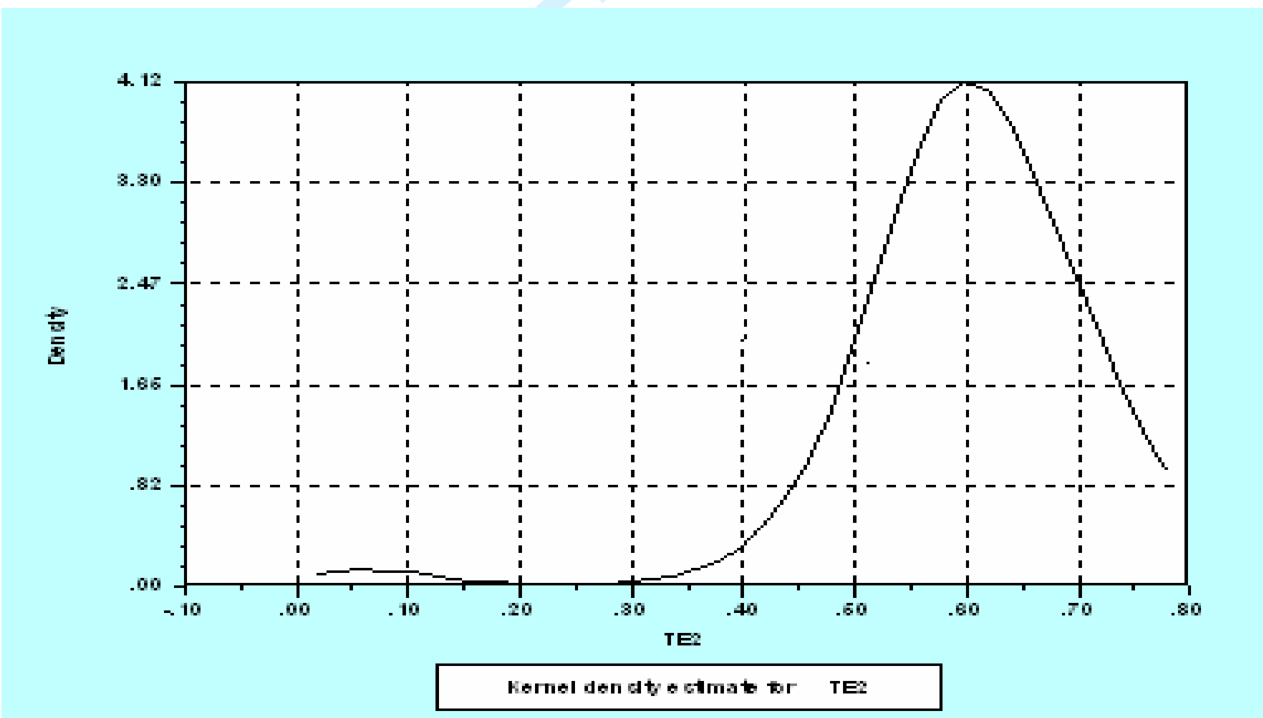


Figure 1c: Kernel Density Estimate for Model 3 Efficiency Values

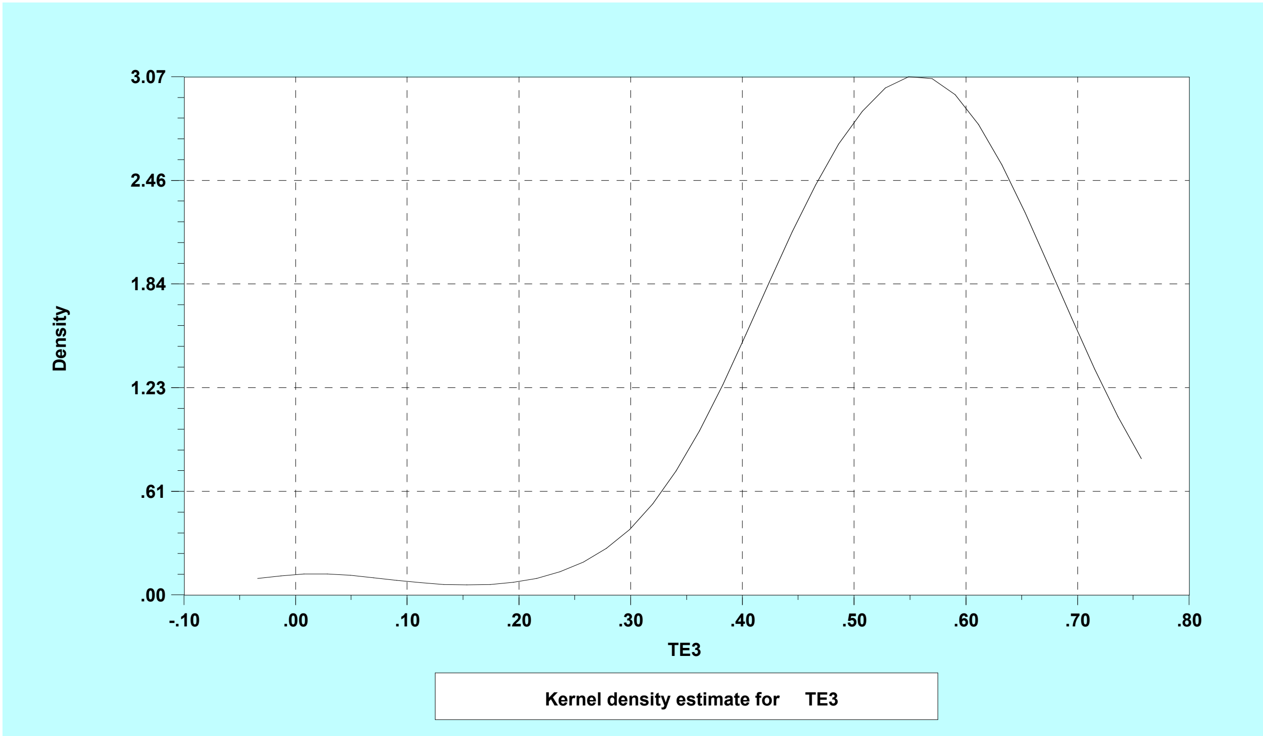
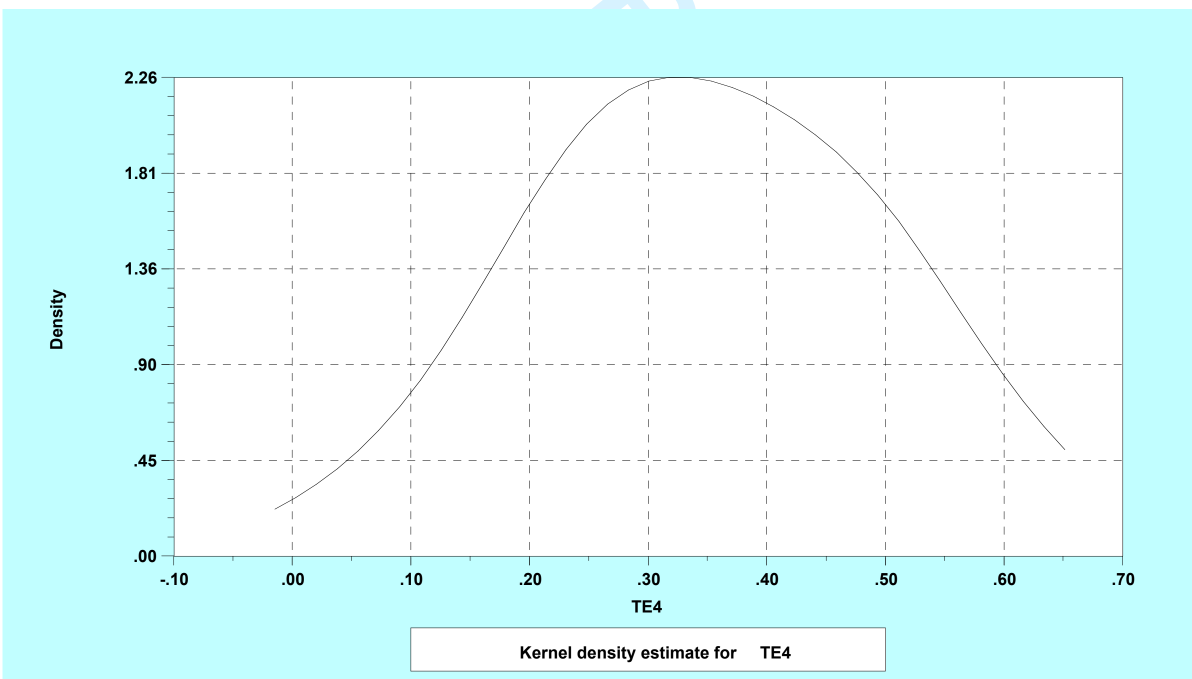


Figure 1d: Kernel Density Estimate for Model 4 Efficiency Values



The shape of the densities associated with model 1, 2 and 3 are similar however model 1 is graphed over a tighter spread of values than the latter two models. The shape and placement of model 4 is different to the other models. This is consistent with the differences we found in the correlations and the rankings. It seems that under fitting the model in any way results in extreme minimum values for some centres (see table 4), suggesting that omitting any of these variables has the potential to distort conclusions based on such results.

Accepting the values emanating from model 1 as correct, the efficiency values produced may be the most favourable but overall they are still unrealistically low. Because these centres are out of hours' emergency primary care facilities, there is a certain element of having a core staff on standby in case they are needed. These staff may be ready for action should an emergency occur but if this emergency is a non-event than this will show up in the inefficiency's as excess capacity when compared to a centre who also had a core staff on the rota that were needed to treat patients in a given evening. It may be useful to consider the paradox that 'not all staff that is idle is inefficient' in future research when considering an emergency service. In addition, given the numerous calls that a co-op receives a night, the potential for a diverse casemix increases, therefore it may also be useful to consider additional techniques to control for casemix. If more exhaustive casemix controls are included it is expected that efficiency values would move closer to 1.

In light of the evidence from our analysis it seems ignoring casemix, quality of care and the hierarchical nature of the data results in efficiency values that are biased downwards in various degrees as expected. Seemingly ignoring any of these factors subsumes their effects into the one sided disturbance, resulting in changes to distributions and ranks of efficiencies.

Discussion:

This analysis considered a SPF where payroll was seen modelled as an output for the centre and the centre's services were seen as the inputs that produced payroll. It was argued that these services are exogenous to the centre. Four models are considered when examining the sensitivity of efficiency values to ignoring quality of care, casemix and the two-tier structure of the data set in this analysis.

Whether casemix should be 'allowed for' in efficiency analysis is open to debate, that is whether a centre that treats patients of a more severe casemix should be expected to overcome this milestone and still be comparable to 'best' practice is questionable. Likewise, it may be argued that quality of care is a 'given' and while members of a medical practice may differ in the manner in which they distribute quality of care these differences level out in the long-term. However, if the latter arguments are to be proven it is important to recognise the potential for such inherent heterogeneity in health care data and study its effects. This analysis argued that such affects are important and ignoring them can sufficiently affect all aspects of the efficiency rankings.

The two-tier structure of this data set, whereby a centre was contained within a co-op, is incorporated into the analysis using a random parameters formulation. It was expected that ignoring any of these affects would bias efficiency estimates down and potentially distort the rankings. Results confirm the latter, in the case of ignoring quality of care the bias in the values and the correlations is far lesser than ignoring casemix. The most extreme changes come from ignoring the two tier structure, correlations are weak, the efficiency values are extremely low and the kernel density illustrations indicate that efficiency values distribution has changed in both shape and spread.

A potential for future research is to consider the low efficiency values emanating from this study further. There are two potential causes for the latter, comparing values across models the reason for low values seems to emanate from under-fitting the model. It would therefore be useful to consider the problem of omitting variables in the context of this data set further. As discussed, the low efficiency results within models may emanate from quite nights in the centre and the core staff being ready for action but not treating many patients. The latter will be subsumed as excess capacity into the inefficiencies and it may be therefore worth while to consider this further. To solidify the latter results more exhaustive measures of casemix may be introduced such as disease classifications or patient age.

Considering the manner in which zeros are handled, sensitivity analysis on efficiency values could be conducted by considering Box-Cox transformations as an alternative. Such sensitivity testing would shed further light on the robustness of these results. It is also possible to extend this analysis to a cross-border study and examine efficiencies for co-op centres in both ROI and Northern Ireland.

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