

Efficiency, heterogeneity and cost function analysis: empirical evidence from pathology services in the National Health Service in England

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Pathology services are increasingly recognised as key to effective healthcare delivery - underpinning diagnosis, long-term disease management and research. To the extent that pathology services affect a patient's treatment pathway, significant healthcare costs are influenced directly by the performance of these services. Given pressures on the UK Department of Health to make efficiency savings and that little is known about the efficiency of pathology laboratories, this area offers unlocked potential for efficiency gains. We adopt a time varying inefficiency model, with laboratory-specific time paths for inefficiency, to identify potential savings in pathology services based on a panel of 57 English laboratories over a five year period. We apply a range of approaches to account for observable and unobservable heterogeneity between laboratories. We find potential efficiency savings of 13% in pathology services in this sample, which implies the potential for an annual saving of £390m in pathology across the NHS. Our study also provides valuable insights into the impact of a range of factors influencing laboratory costs.

I. Introduction

The global financial crisis has increased pressure on public sector expenditure and so on the costs of the healthcare system in the UK. In response to this, the Nicholson Challenge has set out targets for efficiency savings of £20bn by 2015 in the UK National Health Service (NHS) (Health Select Committee, 2010). Financial pressure is expected to extend beyond 2015, with a funding gap of £30bn expected by 2020-21 (NHS, 2013). Thus, ensuring efficiency in all areas of healthcare is key.

There is a body of literature of both academic and other studies (e.g. think tanks such as the King's Fund, see Appleby et al., 2013) that has sought to measure inefficiency in the NHS. These may be at the macro or micro level. Typically, efficiency is measured by stochastic frontiers (SFs), Data Envelopment Analysis (DEA) or multivariate, multilevel modelling (MVML) in the academic literature, and using indicator analysis (such as mortality rates) in the non-academic literature.

At the macro level, the NHS itself is the unit of analysis, and is thus compared to other national healthcare services across the world. In Spinks and Hollingsworth (2009), the UK compared unfavourably (in terms of efficiency) amongst its OECD peers. However, the authors note that theoretical issues limit the interpretation of DEA results. Elsewhere, Smith and Street (2006) argue against the use of SFs at the macro level on theoretical grounds. Greene (2010) takes the view that using microeconomic tools at the macroeconomic level may be inappropriate. Practically, the usefulness of macro efficiency studies is somewhat restricted in the context of this policy challenge because these studies do not indicate where specific savings can be made within the NHS.

At the micro level, hospital studies dominate the national and international literature (Hollingsworth and Parkin, 1999; Jacobs et al., 2006; Hollingsworth, 2003; 2008). Secondary care is the largest tranche of NHS expenditure by far, totalling over £66bn in 2011-2012 (compared to the next largest, primary care, at £21bn) so significant savings potential is likely to reside here; at the same time the wealth of data available means that this is an area already well analysed in the more recent NHS-based literature (Farrar et al., 2009; Laudicella et al., 2010; Cooper et al., 2012; Gutacker et al., 2013; Siciliani et al., 2013; Daidone and Street, 2013). There is work in other areas of service delivery, primary care services for example (Szczepura, 1993; Giuffrida and Gravelle, 2001), however, because the outputs of these services are difficult to define and to measure, eliciting meaningful efficiency scores is challenging (Rosenman and Friesner, 2004; Lester and Roland, 2009; Amado and Santos, 2009; Murrillo-Zamorano and Petraglia, 2011; Longo et al., 2012). Perhaps it is unsurprising, then, that Hollingsworth (2008) finds no recent NHS primary care efficiency studies. The story is similar for other micro level services such as intermediate care.

Although there is a wide literature assessing efficiency performance of the NHS, new research is required since further gains are needed to meet the Nicholson Challenge. It has been argued that ‘easy’ efficiency savings have now been made across the NHS (National Audit Office, 2012). Further, surveys of NHS finance directors reveal growing scepticism about whether the Nicholson Challenge will be met at all (Appleby et al., 2013). Indeed, there is concern that financial pressure will continue beyond 2015 (Roberts et al., 2012). We therefore see potential in analysing diagnostic services which support healthcare delivery as an unturned rock to find new efficiency gains to contribute to the top-level policy goal. Specifically, we focus on pathology.

Pathology services account for an estimated 3-5% of the overall NHS budget, costing an estimated £2.5bn in 2005 (Department of Health, 2006). Although relatively small as a proportion of total health care spend, potential efficiency gains in these services are not limited to pathology itself. Pathology activity supports many front-line services and so savings in pathology services promote further gains elsewhere in the healthcare system (Veronesi et al., 1997; Buckell et al., 2013). The Carter Review (Department of Health, 2006) estimates 70-80% of all clinical decisions are affected by pathology analyses; thus good pathology practice can lead to cost savings along a patient's treatment pathway (Department of Health, 2006). There is evidence of unnecessary repeat testing (for example when, according to NICE¹ guidelines, insufficient time has elapsed to make a judgement on a condition so a second test is required) (Department of Health, 2006), suggesting that inefficient practice is present in these services. Lastly, there is variation in the uptake of lean practice initiatives² meaning that there is likely variation in the magnitudes of efficiency in these services. Therefore, there are likely significant gains to be made by encouraging best practice in pathology services to contribute to the policy objective of achieving efficiency savings. This study aims specifically to identify the level of inefficiency in pathology services in order to measure the extent of savings possible in this area.

The current approach to measuring inefficiency in pathology in the NHS is performance indicator analysis (such as cost per test carried out); (Healthcare Commission, 2007; Department of Health, 2008; Liebmann, 2011; Holland et al., 2012). These are partial measures which do not fully reflect all the factors affecting the costs of provision under different circumstances (for example, scale properties or sources of operational heterogeneity between providers). This point has been established in the wider health context (Goddard and

¹ National Institute for Clinical Excellence

² NHS Institute for Innovation and Improvement: Pathology lean practice case studies, http://www.institute.nhs.uk/quality_and_value/lean_thinking/lean_case_studies.html

Jacobs, 2009; Street et al., 2011). We use the data collected and analysed by the Keele University Benchmarking Unit (Holland et al., 2012), but extend the analysis by utilising an econometric framework to give a single measure that captures the overall efficiency of pathology services. Our model takes account of a range of factors influencing costs, whilst controlling for unobservable heterogeneity.

We use SFs which are applied widely in health at the micro level (Street, 2003; Farsi and Filippini, 2005, 2008; Herr, 2008; Hollingsworth, 2008; Olsen and Street, 2008; Rosko & Mutter, 2008; Sorensen et al., 2009; Herr et al., 2011). To our knowledge, no SF (or other efficiency measurement tool such as DEA) work has been conducted on pathology laboratories, meaning that our application is the first of its kind³.

The remainder of this paper is set out as follows. In section 2 we review the existing literature on pathology performance and argue that an econometric framework can offer a useful extension to these analyses. In section III we set out our methods, data and empirical specification. In section IV we give our results, in section V we discuss our results, and in section VI we conclude.

II. Performance Measurement in pathology

Pathology services are increasingly recognised as key support across the NHS. As demand for NHS services increases in general, demand for pathology services increases (as derived demand). Faced with increasing demand and falling income (Department of Health, 2006), the performance of pathology services is coming under ever-increasing scrutiny. Therefore,

³ If pathology is classed as diagnostic medicine, then there exists some SF work in this area (Dismuke & Sena, 1999). However, this study concerns patient-based, in-hospital activity such as computerised axial tomography (CAT) scans, whereas our study involves pathology laboratories – which are independent of their host hospitals and do not have direct patient contact – conducting blood and tissue tests. We therefore view pathology services as differentiable from this kind of diagnostic medicine.

rigorously measuring the performance of laboratories is critical. Typically, pathology laboratories are situated within NHS trusts (see below).

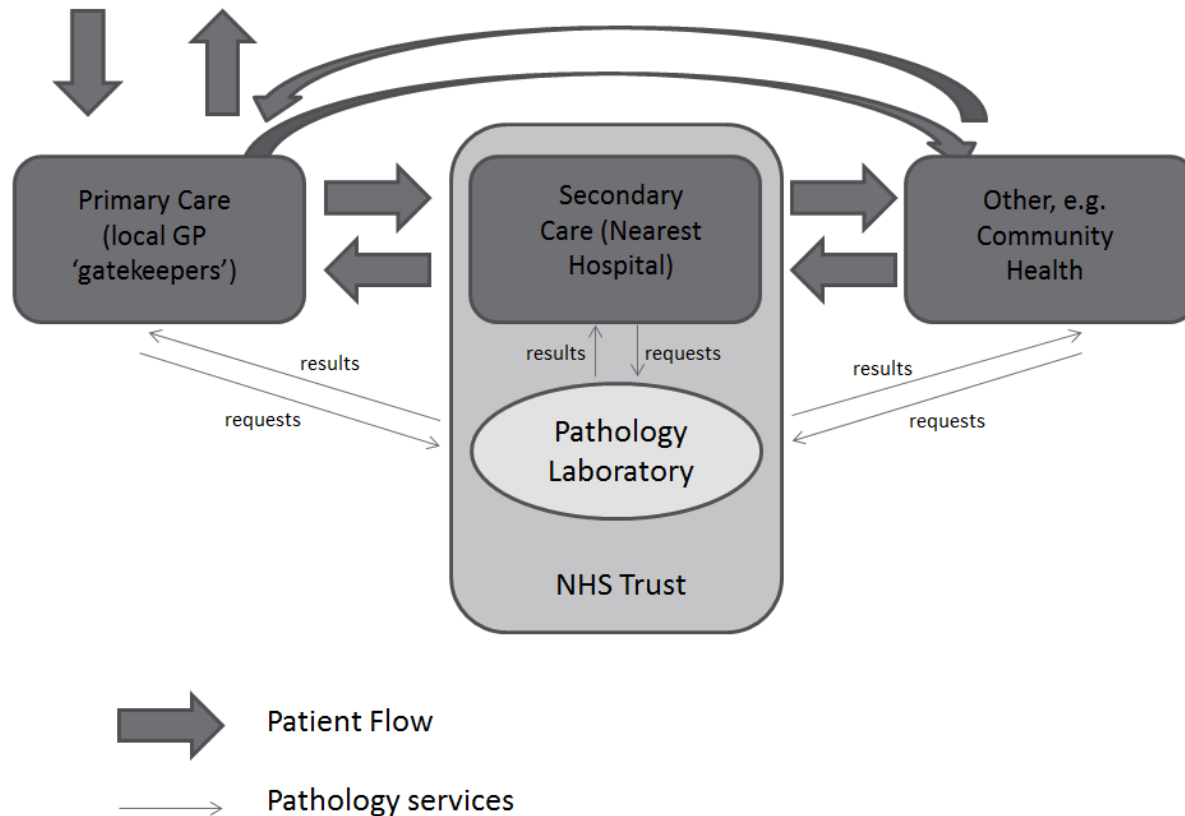


Fig. 1: Schematic of pathology services

As can be seen from Fig. 1, as patients move around the healthcare system, diagnostic services are requested and performed. As activity occurs, information is recorded and used for analysis of these services.

Major reviews of NHS pathology services include the Carter Report (Department of Health, 2006), and the associated follow up report which included pilot studies of services (Department of Health, 2008); the Healthcare Commission's study (2007); the NHS confederation (2010); and the Keele University Benchmarking project (Holland et al., 2010;

2011; 2012)⁴. There is a growing body of evidence on these services, and good quality data available; a summary of these studies' analyses is provided in Table 1.

⁴ Some key performance indicators are being introduced, but have not yet been employed (Liebmann, 2011).

Study	Year	Number of Sites	Type of study	Summary of Key Points
Department of Health	2006	163	Qualitative	Full qualitative analysis of pathology services. Identified key areas for performance improvement - workforce balance, economies of scale, information systems adoption, out of hours working, network activity. Recommended pilot studies conducted. Noted that geographical location may be a source of cost heterogeneity.
Healthcare Commission	2007	163	Quantitative	Breakdown by pathology discipline comparative cost per test analysis; requests:staff and tests:staff ratios used; descriptive statistics for out of hours operation, information systems adoption, use of automated services, network activity; recognised that tests for primary care may be cheaper than for secondary care; noted the issue of tests:requests as a potential source of performance variation. Foundation trusts may take a commercial approach to service provision.
Department of Health	2008	12	Quantitative	Breakdown by pathology discipline (e.g. biochemistry) comparative cost analysis; some economies of scale observation; little control for heterogeneity; savings estimate £250m (extrapolated results nationally from 12 pilot studies).
NHS Confederation	2010	163	Qualitative	Identifies variation in practice; difficulty in monitoring staff leads to variation in practice; workforce balance, IT systems adoption, leadership and network activity as key areas for performance improvement.
Keele Benchmarking	2012	84	Quantitative	Breakdown by pathology discipline (e.g. biochemistry, hystocytology); test volumes descriptive statistics; productivity indicators; 5 year trend analysis of outputs and productivity indicators; expenditure of laboratories; quality indicators (e.g. turnaround times)

Table 1: Pathology literature

Table 1 describes the outcomes of each of the studies. The quantitative analyses above use performance indicators to judge the performance of NHS pathology laboratories (e.g. cost per test ratios, staff per test, turnaround times, test to request ratios). The use of these indicators is widespread in NHS pathology and across the world (Valenstein et al., 2001; Kiechle and Main, 2002), but there are limits to their ability to reflect the entire operation of a laboratory. Moreover, in health markets, indicators can be targeted for gaming (Propper and Wilson, 2003; Propper et al., 2008; Mutter et al., 2008; Palangkaraya and Yong, 2013), or relying solely on indicators can lead to unintended consequences (Bird et al., 2004; Cots et al., 2011). Lastly, judging a single unit's performance across several indicators may be difficult if the values conflict.

An econometric framework is proposed to overcome these issues. Our measure of cost efficiency yields a single efficiency score capturing overall performance which is easily interpreted (bounded by zero and one). Gaming is no longer an issue since the entire production process is modelled⁵.

Further key advantages of the econometric approach are that econometric analyses are underpinned by extensive economic theory and are used widely across many sectors, including health (Kumbhakar and Lovell, 2000; Hollingsworth, 2008). In addition, we can analyse the temporal pattern of laboratory inefficiency, which NHS staff have indicated as a desirable feature of performance analysis (Hollingsworth and Peacock, 2008). Finally, econometric analysis allows us to value the impact of some of the issues noted in the qualitative studies (Table 1), such as the ratio of primary care tests on costs – as raised in the Healthcare Commission study (2007), which is useful information in the policy context.

⁵ We use operating costs rather than total costs (including capital charges), meaning the production process is not strictly entirely modelled. However, capital costs are allocated at trust level, meaning this is often arbitrarily and inconsistently carried out and may therefore confound efficiency scores.

III. Methods

Stochastic frontiers (Aigner et al., 1977; Meeusen and van Den Broeck, 1977) are econometric tools used to estimate the level of inefficiency of firms or decision making units (DMU) in a sample. Laboratory costs are our metric of interest. Our SF for pathology takes the form,

$$c_{it} = \alpha_0 + f(y, w, z, q, t; \beta, \theta) + u_{it} + v_{it}; \quad i = 1, 2, \dots, N, \quad t = 1, 2, \dots, T \quad (1)$$

Where i indexes individual units (laboratories) and t indexes time periods. c_{it} are costs of laboratory i in time period t ; y is a $k \times 1$ vector of output; w is a $k \times 1$ vector of input prices; z is a $k \times 1$ vector of observable heterogeneity variables; q is a $k \times 1$ vector of service quality; t is time; θ is the time trend parameter; and β is a $k \times 1$ vector of parameters to be estimated. Random statistical noise is captured by v_{it} and inefficiency is u_{it} ; see table 2 for specific models.

As standard in the literature, output and input prices are considered exogenous, which is obvious for input prices and reasonable for outputs given that the laboratories do not choose their level of output. In the case of pathology, using the work of previous studies (see table 1), the operational characteristics of the pathology operating environment can be identified and variables are used to capture these where data are available (the z vector). Otherwise, methods for capturing unobservable heterogeneity are employed. Given that measures of quality in pathology services are not as complex as in the treatment of patients (Smith and Street, 2013 discuss the multi-dimensional nature of patient treatment quality), in this study quality is taken as given, since each of the laboratories in the sample has acquired quality accreditation⁶.

⁶ Clinical Pathology Accreditation: <http://www.cpa-uk.co.uk/>

A set of five models SF is used to model inefficiency. These include a generalised least squares random effects model (REM)⁷; see Kumbhakar and Lovell (2000); a Pitt and Lee (1981) (P&L) stochastic frontier with time invariant inefficiency; a Battese and Coelli (1992) (BC92) frontier with time varying inefficiency; a Cuesta (2000) (Cuesta) frontier with firm-specific (or in our case, lab-specific) time-varying inefficiency; and a true random effects model (TRE) (Greene, 2005). See table 2 for details.

The REM is used to give ‘baseline’ values for both parameter estimates and for inefficiency (using the GLS procedure outlined in Kumbhakar and Lovell (2000)). Parameter estimates from these models do not rely on the distributional assumptions of the SFs⁸ and so parameter estimates are used to validate those derived from the frontiers.

The P&L model assumes time-invariant inefficiency. The BC92 fits a time trend to the inefficiency - the η parameter (table 2) - which subjects all firms’ efficiency scores to a common direction of change over time. The Cuesta model is a generalisation of this, allowing estimation of independent firm efficiency time trends: individual η s for each laboratory⁹. This means firms can ‘catch up’ relative to others over time and the efficiency rankings of the laboratories can change over time, which are realistic features. Alvarez et al. (2006) note that a key advantage of this model is that it enables the unrealistic assumption of independence in inefficiency over time (a problem that plagues many comparator models) to be relaxed.

The TRE model claims to delineate efficiency from unobservable heterogeneity by including a time-invariant, firm-specific term in the model to capture unobserved factors, in addition to the inefficiency term (Greene, 2012a). A potential drawback of this model is that efficiency scores are independent over time, meaning that time trends of firms cannot be tested

⁷ Hausman tests (1978) consistently favoured RE over FE estimation.

⁸ Due to an unbalanced panel, a Baltagi & Li (1990) adaptation of the Breusch-Pagan (1980) test has been used and confirms the use of panel methods.

⁹ Within this framework, the temporal pattern of inefficiency can be tested statistically, which is a key advantage over alternative approaches such as Cornwell et al. (1990).

statistically. Additionally, this model assumes that all the time-invariant variation in the cost function that is not explained by the regressors is unit-specific heterogeneity and not inefficiency; this is not necessarily the case as some time invariant persistent inefficiency may also be present.

To these models, we test three alternative specifications to examine heterogeneity. First, a basic cost function with output, input prices and time is estimated. By including a time trend in the cost function, we separate exogenous change in costs over time from cost inefficiency (Kumbhakar and Lovell, 2000).

In the second, we add the vector, z , of observable heterogeneity variables. These include the number of primary care tests (which are thought to be less costly than other tests), and the test to request ratio which captures the variation in the number of tests per request, which varies between laboratories, and is therefore a source of heterogeneity. Another source is the geographical setting of the laboratory: metropolitan, urban or rural (following Department of Health, 2006, see table 1). This will be referred to as the TYPE of laboratory. It has been suggested that pathology demands of inner city laboratories are much different to those in rural areas. Further, the foundation status of each trust is seen to motivate trusts to act more commercially (Healthcare Commission, 2007, see table 1), which is expected to be extended to their pathology services. Lastly, data are available on whether the laboratories provide teaching services.

The third specification finally adds dummy variables to capture unobservable heterogeneity (e.g. IT infrastructure/maturity, network activity) (Arocena et al., 2012). We use the strategic health authority dummy variables and then group them by region for parsimony.

We refer to the specifications as s(i), s(ii) and s(iii).

Finally, after having used this testing process to select a model, we exploit the fact that the SF framework is based on a cost function to examine the cost elasticity properties across the output range and derive average and marginal costs in pathology production (AC and MC hereafter). We note that this is a key advantage of this method over DEA as an alternative. Focus is given to this aspect of production because this is a popular theme of interest throughout the literature (table 1) and because of the growing membership of laboratories to local networks, which is encouraging the pooling of output); see Department of Health, 2011.

Empirical Specification

A translog functional form is used to best approximate the economic model. The translog is preferred for its flexible nature - it provides a second-order differential approximation to any unknown function $f(\cdot)$ (as in Equation (1)) (Kumbhakar and Hjalmarsson, 1995), it does not impose restrictions on substitution possibilities, and allows economies of scale to vary with output levels (Christensen and Greene, 1976).

Logarithms are taken to give Farrell (1957)-type radial measures of inefficiency¹⁰. The translog representation is estimated for each model,

$$\begin{aligned}
& \ln c_{it} \\
&= \alpha_0 + \sum_{n=1}^1 \beta_n \ln y_{it} + \frac{1}{2} \sum_{n=1}^1 \beta_{nn} (\ln y_{it})^2 + \sum_{a=1}^1 \beta_a \ln wl_{it} + \frac{1}{2} \sum_{n=1}^1 \beta_{aa} (\ln wl_{it})^2 \\
&+ \sum_{b=1}^2 \beta_b \ln z_{it} + \frac{1}{2} \sum_{n=1}^2 \beta_{bb} (\ln z_{it})^2 + \sum_{n=1}^1 \sum_{a=1}^1 \beta_{na} \ln y_{it} \cdot \ln wl_{it} + \sum_{n=1}^1 \sum_{a=1}^2 \beta_{na} \ln y_{it} \cdot \ln z_{it} \\
&+ \sum_{a=1}^1 \sum_{b=1}^2 \beta_{ab} \ln wl_{it} \cdot \ln z_{it} + \sum_{c=1}^4 \beta_c z_i + \sum_{d=1}^3 \beta_d \omega_r + \theta_1 t + \theta_2 t^2 \\
&+ \varepsilon_{it}
\end{aligned} \tag{2}$$

¹⁰ Variables are mean scaled to allow direct interpretation of the first order terms.

Where c_{it} are operating costs; y_{it} is output; wl_{it} are labour input prices; z_{it} are exogenous variables including tests for primary care and the test to request ratio; z_i are firm specific, time-invariant dummy variables for foundation status, teaching status and laboratory type; ω_r are regional dummy variables to capture unobservable heterogeneity; and t is a time trend capturing real cost changes over time (in this sample). Then, ε_{it} is decomposed into u_{it} and v_{it} which are inefficiency and statistical noise, respectively (see table 2 below for detailed specifications of each model).

To decide on a preferred model, a number of statistical tests are applied¹¹. We test functional form using a Wald test¹².

Next, we test between the three specifications from above, by which we mean either no heterogeneity variables s(i); observable heterogeneity variables only s(ii); and observable and unobservable heterogeneity variables¹³ s(iii). We use LR tests for this. We refer to this as TEST 1.

We then test between each efficiency model, by which we mean one of the 5 different efficiency models (REM, P&L, BC92, Cuesta, TRE), using a LR test¹⁴ for nested models (which we refer to as TEST 2) and a Vuong test (1989) for non-nested models¹⁵ (which we refer to as TEST 3).

In total, there are 30 models to be estimated¹⁶. 15 models are reported for comparison. LIMDEP software (Greene, 2012b) is used for estimation.

¹¹ Lai and Huang (2010), pp. 3, lament that “there are only limited systematic treatments of tests or model selection criteria in the existing SF literatures.”

¹² H_0 : additional translog terms (squared and cross terms) are jointly equal to zero.

¹³ H_0 : observable or unobservable heterogeneity variables are jointly equal to zero.

¹⁴ H_0 : log likelihood model (a) is equal to log likelihood model (b)

¹⁵ H_0 : model (a) is equal to model (b)

¹⁶ 2 (functional forms) x 3 (heterogeneity variable specifications) x 5 (types of efficiency model)

	REM	P&L	BC92	CUESTA	TRE
Firm-specific component, α_i	$iid(0, \sigma_\alpha^2)$	$iid(0, \sigma_\alpha^2)$	$iid(0, \sigma_\alpha^2)$	$iid(0, \sigma_\alpha^2)$	$N(0, \sigma_\alpha^2)$
Random Error, ε_i	$iid(0, \sigma_\varepsilon^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N(0, \sigma_u^2) $ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N(0, \sigma_u^2) $ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N(0, \sigma_u^2) $ $v_{it} \sim N(0, \sigma_v^2)$	$\varepsilon_{it} = u_{it} + v_{it}$ $u_{it} \sim N(0, \sigma_u^2) $ $v_{it} \sim N(0, \sigma_v^2)$
Inefficiency	$\hat{\alpha}_i - \min\{\hat{\alpha}_i\}$	$E[u_{it} u_{it} + v_{it}]$	$E[u_{it} u_{it} + v_{it}]$	$E[u_{it} u_{it} + v_{it}]$	$E[u_{it} \alpha_i + \varepsilon_{it}]$
Time Trend			$u_{it} = \exp[\eta(t - T)]. u_i$	$u_{it} = \exp[\eta_i(t - T)]. u_i$	

Table 2: Econometric Specifications of models

Data

Annual pathology benchmarking data (Keele Benchmarking) is used to compile an unbalanced panel of 57 English NHS pathology laboratories during a 5 year period from 2006/7 to 2010/11¹⁷; accordingly we use maximum likelihood estimation (Baltagi, 2008) (except the REM which uses GLS and the TRE which uses simulated maximum likelihood). The sample represents approximately one third of the 163 NHS pathology laboratories in England. From table 3, there is considerable variation in the range and standard deviation of the costs, tests and requests variables, giving us confidence that we have a broad sample of laboratories. There is an almost even spread of laboratories amongst strategic health authorities (and therefore across England).

Our data is for biochemistry services only. Biochemistry is one of five disciplines of pathology (the other four being haematology, hystocytology, immunology and microbiology). Biochemistry is chosen because it is highly mechanised thus diminishing the issue of heterogeneity for modelling. It is the largest area of pathology (around 70% total activity (Holland et al., 2011)) and all laboratories run biochemistry services.

¹⁷ Number of observations over time of laboratories: t=2: 27, t=3: 7, t=4: 2, t=5: 21

Variables include total operating costs (net of capital charges), output (through number of tests and number of requests), input prices of labour (from the UK labour force survey) and exogenous variables including the number of tests for general practice (primary care) and dummy variables for the foundation status of the host trust, for the pathology service providing teaching, for the laboratory type (metropolitan, urban, rural) and for the strategic health authority in which the pathology service is located. Service quality is assumed given that laboratories have been accredited as noted earlier.

Costs and wage data are in real terms (2007 prices) using the consumer prices index. Labour force survey data is chosen over other sources (NHS staff census data, for example). This is firstly to ensure the exogeneity of the data¹⁸. Secondly we aim to better reflect the regional variation in labour input prices than would be possible using alternative data. The ratio of tests to requests is calculated from the data. Strategic health authorities are, following initial modelling, combined to form regional dummy variables for London, the South, the Midlands and the North using a Wald test procedure (Greene, 2012a).

Variable	Mean	S.D.	Min	Max
Operating costs (adjusted)	3617320	2058358	963875	11741895
Number of tests	5037362	2990846	1380384	30199502
Number of requests	714125	465535	191078	4423531
Input prices (Labour) (adjusted)	24551	4160	15834	49955
Number of primary care tests	2059689	932794	380790	5480395

Table 3: Descriptive Statistics

¹⁸ Mutter et al. (2013) demonstrate using healthcare data that endogeneity can bias efficiency scores.

IV. Results

Cost function parameters

Across the range of models estimated (table 4), a number of observations can be made. Cost elasticity with respect to output implies economies of scale in pathology production (the first order parameters are elasticities at the sample mean; we go on to explore how these vary with output later in this section). Real operating costs appear to be decreasing over time as indicated by the negative coefficient on the time trend variable. Operating costs in pathology laboratories are higher for those which have high test to request ratios, are located in metropolitan and urban locations (relative to rural laboratories), provide teaching services and are in the Midlands (relative to the Northern laboratories). Operating costs are lower for foundation trust laboratories and for those located in London or the South (relative to the North). There was no clear finding as to the effect of GP tests on laboratory operating costs, where the effect appears negative in two models, positive in another and not statistically significant in any other.

Statistical testing and inefficiency model selection

Wald tests strongly and consistently favoured the translog functional form. Test 1 finds the s(ii) and s(iii) heterogeneity variables jointly significant additions to the models in all cases (table 5). Test 2 strongly favours the Cuesta model over the BC92 and P&L. Test 3 favours the Cuesta model over the TRE model¹⁹. Therefore our preferred inefficiency model is Cuesta

¹⁹ We are aware that the Vuong test has no degrees of freedom restriction, meaning that it imposes no penalty for additional parameters estimated and so is likely to, in this case, favour the Cuesta model which has more parameters than the TRE model. Therefore, as a robustness check, we have also tested the P&L (which has fewer parameters than the TRE) against the TRE, and the test favours the P&L. Because our LR test preferred the Cuesta to the P&L, and the Vuong preferred the P&L to the TRE, we prefer the Cuesta to the TRE.

s(iii) based on statistical criteria. Indeed, this model is preferred a priori because of how it deals with efficiency change over time (see section III for details). A significant lambda value (table 4) confirms the presence of inefficiency²⁰.

²⁰ In addition, we have tested the presence of inefficiency using the LR test procedure outlined in Coelli et al. (2005) pp.258, which also confirms our result, but we do not report the test results here.

Dependent Variable: Operating cost (OPEX)	Specification s(i) c = y, w Model					s(ii) c = y, w, z – observable					s(iii) c = y, w, z - observable, z - unobservable				
	REM	P+L	BC92	CUESTA	TRE	REM	P+L	BC92	CUESTA	TRE	REM	P+L	BC92	CUESTA	TRE
	PARAMETER VALUES														
CONSTANT	6.55***	6.32***	6.31***	6.31***	6.60***	6.55***	6.40***	6.39***	6.39***	6.61	6.53***	6.42***	6.42***	6.35***	6.54***
OUTPUT	0.43***	0.29***	0.31***	0.30***	0.74***	0.67***	0.55***	0.62***	0.35***	0.99***	0.67***	0.58***	0.64***	0.44***	1.04***
INPUT PRICES	0.61***	0.52**	0.54**	0.68***	0.64***	0.64***	0.53***	0.49**	0.59***	0.84***	0.83***	0.80***	0.89***	1.30***	-0.08***
YEAR	-0.01**	-0.01	-0.01	-0.01**	-0.02***	-0.01**	-0.01*	0.01	-0.01	-0.01	-0.01**	-0.01*	0.01	-0.01***	-0.01***
GP_TESTS						0.01	0.03	0.02	0.07*	-0.14***	0.01	0.02	0.03	0.06	-0.08***
TES:REQ						0.23***	0.19**	0.21***	0.02	0.47***	0.24***	0.21***	0.21***	0.12**	0.48***
TYPE: METROPOLITAN						0.13***	0.14***	0.14***	0.15***	0.09***	0.14***	0.15***	0.15***	0.16***	0.10***
TYPE: URBAN						0.03	0.04*	0.04	0.05*	0.01	0.02	0.02	0.01	0.02	0.01***
FOUNDATION						-0.06**	-0.07***	-0.07***	-0.11***	-0.06	-0.04	-0.06**	-0.06***	-0.07***	-0.04***
TEACHING						0.03	0.04*	0.03	0.01	0.01	0.04	0.05**	0.03	0.02	0.03***
REGION: LONDON											-0.02	-0.05	-0.07**	-0.16***	-0.02***
REGION: SOUTH											-0.03	-0.04	-0.05*	-0.01	-0.01***
REGION: MIDLANDS											0.08**	0.10***	0.09***	0.10***	0.08***
EFFICEINCY FIGURES															
mean	0.71	0.81	0.81	0.79	0.99	0.76	0.87	0.88	0.82	0.00	0.77	0.90	0.90	0.87	0.00
s.d.	0.10	0.11	0.11	0.12	0.00	0.08	0.08	0.08	0.11	0.00	0.07	0.07	0.07	0.10	0.00
lambda		5.11***	5.17***	13.01***	3974.52		3.15***	3.33***	11.97***	0.00		2.67***	3.04***	8.38***	552028
eta			-0.01					-0.07*					-0.11**		

Table 4: Estimation outputs

Notes: *,** and *** denote significance at the 10%, 5% and 1% level, respectively.

LR Statistic Tests for Heterogeneity Variables: TEST 1

Model		P&L	BC92	CUESTA	TRE
Restriction of S(ii) to S(i): Observable heterogeneity variables	(d.f.: 13,13,13,12)	44.6***	48.00***	44.82***	91.04***
Restriction of S(iii) to S(ii): Unobservable heterogeneity variables	(d.f.: 3,3,3,4)	14.86***	17.70***	8.38***	38.60***

LR Statistic Tests for Model Selection (nested models only): TEST 2

			CUESTA v. P&L	CUESTA v. BC92
Specification (i): Basic Cost function		(d.f.: 57, 56)	166.84***	166.70***
Specification (ii): Observable Heterogeneity		(d.f.: 57, 56)	167.00***	163.32***
Specification (iii): Regional Dummies for Unobserved Heterogeneity		(d.f.: 57, 56)	160.52***	154.00***

Vuong Test Statistic: TEST 3

TRE specification (iii) vs. Cuesta model specification (iii)	V = -9.066***
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Model Log Likelihood Function Values and degrees of freedom (K)

Model	P&L	BC92	CUESTA	TRE
Specification (i): Basic Cost function	198.80	198.97	282.22	135.81
K	9	10	66	10
Specification (ii): Observable Heterogeneity	221.13	222.97	304.63	181.33
K	22	23	79	23
Specification (iii): Regional Dummies for Unobserved Heterogeneity	228.56	231.82	308.82	200.63
K	25	26	82	26

Table 5: LR specification and model selection

Notes: *,** and *** denote significance at the 10%, 5% and 1% level, respectively.

Inefficiency estimates

From table 4, the mean inefficiency estimate from our preferred model is 0.87. On average, efficiency is computed as decreasing slightly amongst pathology laboratories over time (which is in agreement with the BC92 models in table 4) from 0.87 in 2007 to 0.86 in 2011. Fig 2 shows the cost efficiency estimates of laboratories over time. The bar in Fig. 2 is at efficiency = 1, i.e. full efficiency. Groups of points correspond to each individual laboratory, e.g. observations 1-5 are the efficiency estimates for laboratory 1 in years 1 to 5, observations 6 to 10 are laboratory 2 in years 1-5, and so on. We do not find the problem of efficiency scores dropping-off the frontier in the final year of the sample, which has been a concern for other applications of this model (Wheat and Smith, 2012). In addition, we find that many of the laboratory-specific η s are statistically significant. Those that were not tended to be the firms that are on the frontier (and thus have little or no inefficiency change over time), which can be seen in figure 2.

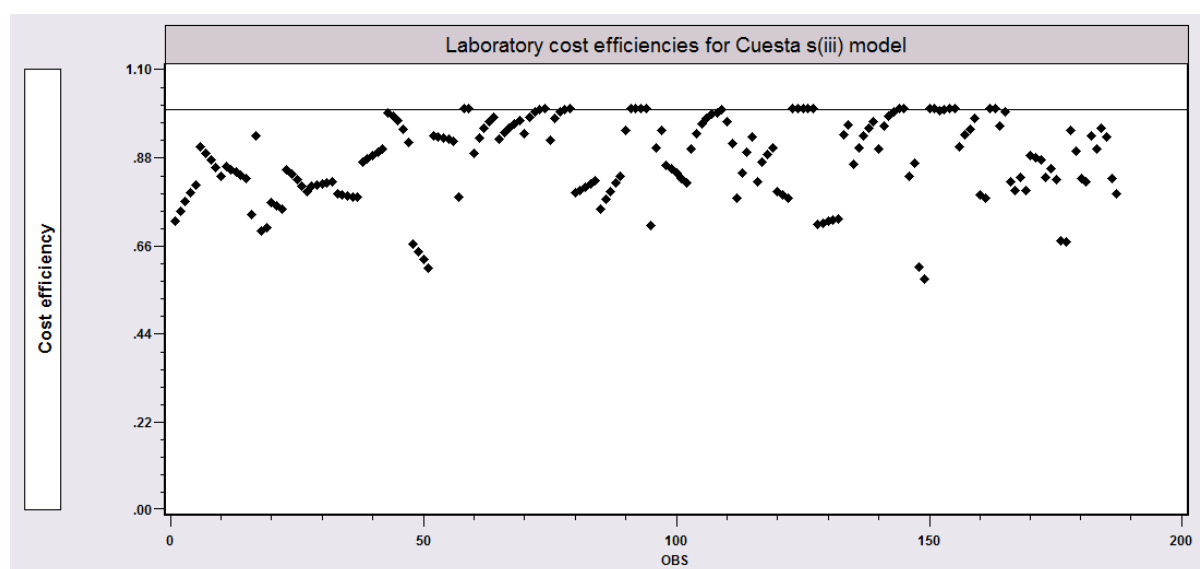


Fig. 2: Laboratory cost efficiency estimates over time

Elasticity of cost, average and marginal costs

Our set of models give estimates of the elasticity of cost with respect to output at the sample mean in the range of 0.29-1.04 (table 4) and is 0.44 in the preferred model. However, a more

informative approach is to examine how this elasticity changes with the scale of the operation, proxied by output (Fig. 2), using our preferred model. Using this elasticity, we are able to further estimate AC and MC per request using fitted values from the model (see Wheat and Smith, 2008, for details) (Figs 4 and 5).

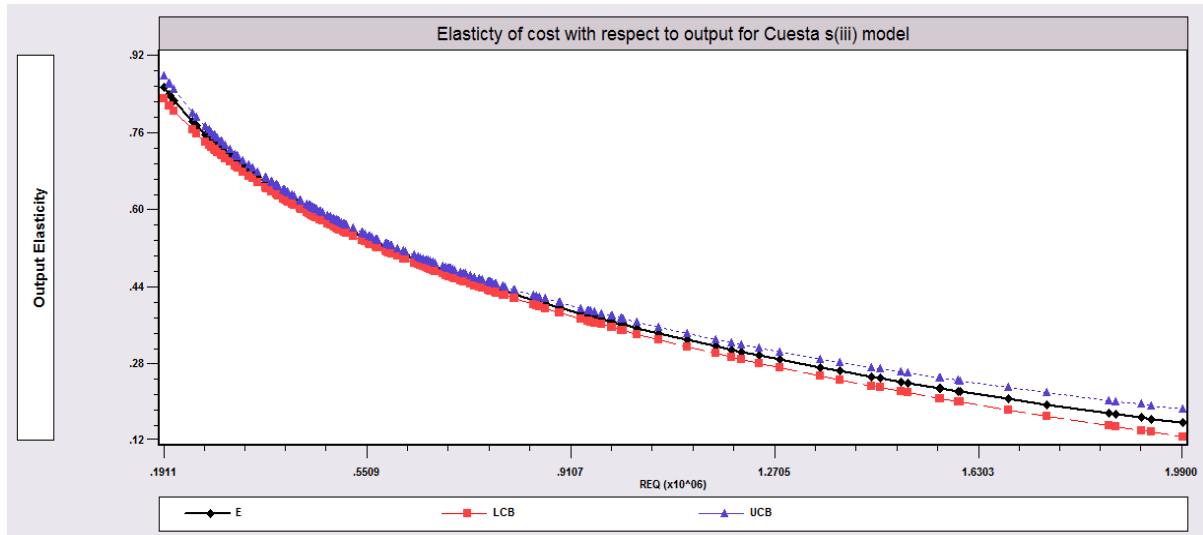


Fig. 3: Elasticity of cost with respect to output for Cuesta s(iii) model

Note to Figure 3: LCB – lower confidence bound, UCB – upper confidence bound. Requests are varied, all other variables are held at the sample mean.

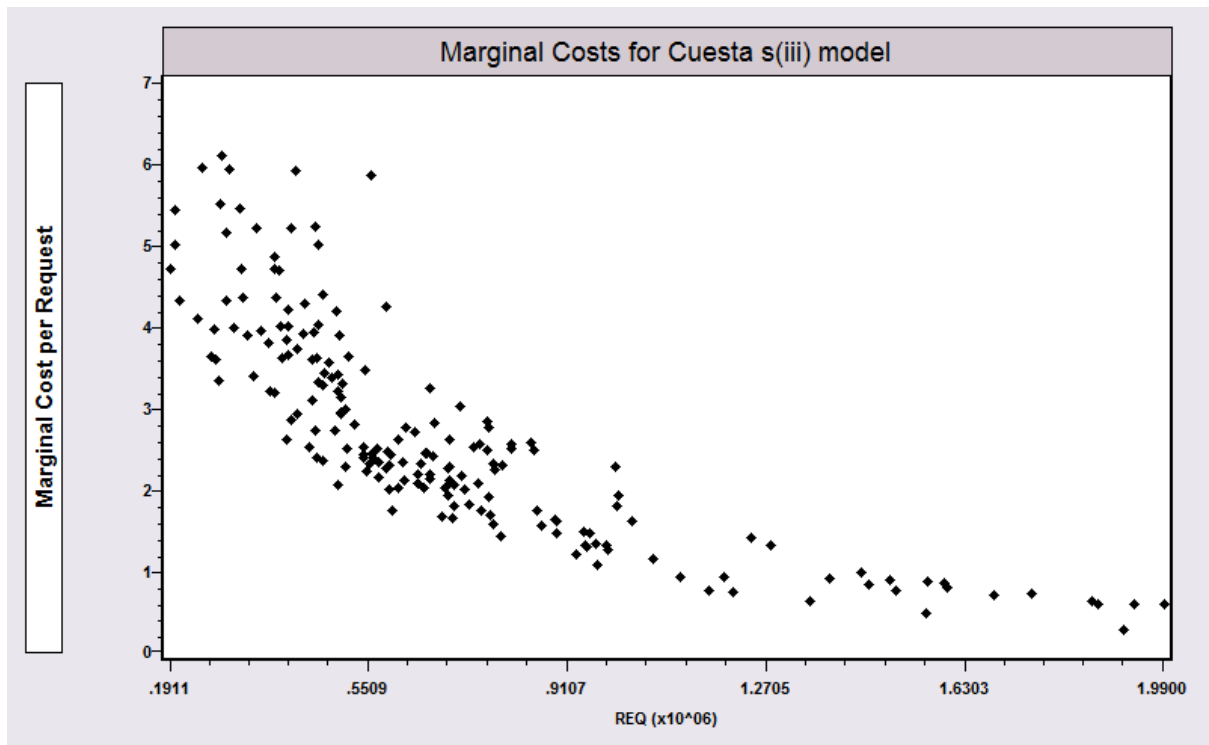


Fig. 4: Marginal cost (MC) for Cuesta s(iii) model

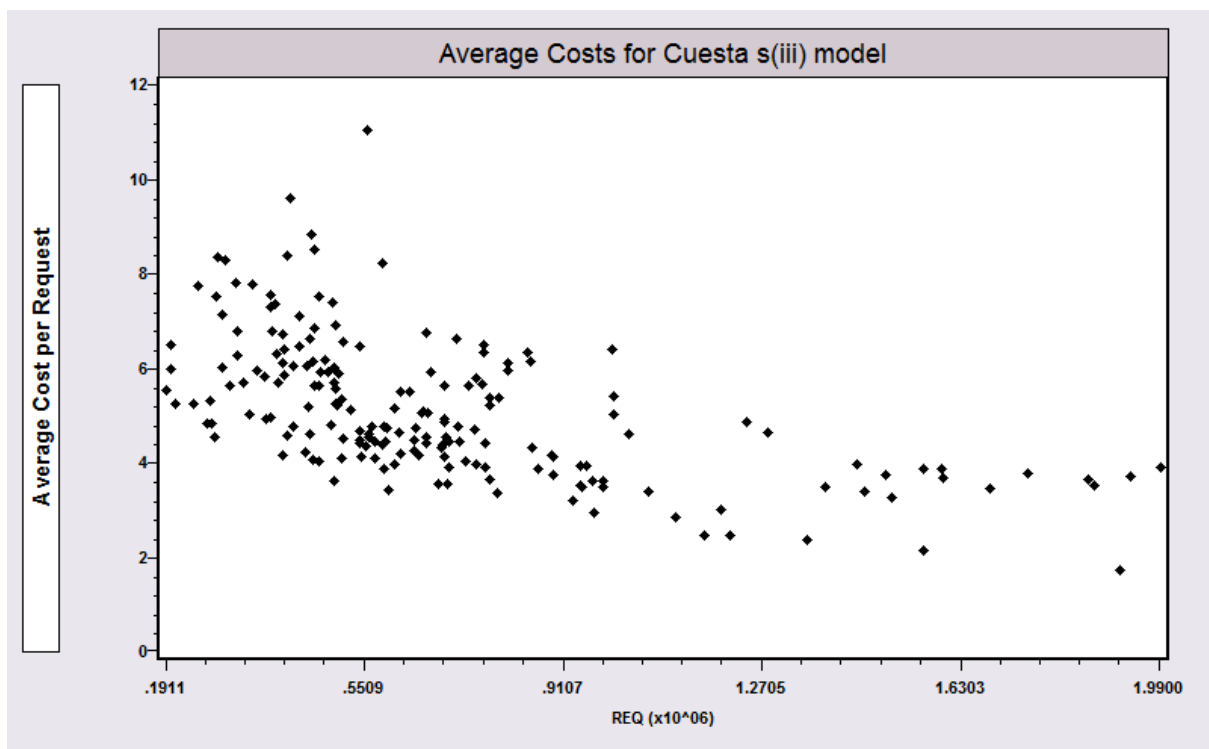


Fig. 5: Average cost (AC) for Cuesta s(iii) model

V. Discussion

Cost function parameters

The parameter estimates in the frontier models show reasonable concordance with each other and with the REM model, giving us confidence in our models.

The time trend coefficients suggest a reduction in real laboratory operating costs of 1-2% per year. The 1-2% figure can then be seen as the shifting of the frontier over time. It may be decreasing if, for example, productivity in pathology production is increasing, which would support the findings of Holland et al., (2012).

Moving to the observable heterogeneity parameter coefficients (s(ii) variables), there was no clear finding of the impact of GP tests (the parameter was not statistically significant). From the healthcare commission (2007), a negative coefficient value was expected because primary care tests are thought to be cheaper than other tests.

The tests to requests ratio coefficients are in line with a priori expectations (positive and less than 1) from the literature (table 1). The estimated elasticity from this sample is in the range 0.19-0.48. The implications depend on the interpretation of this practice – it may be considered gaming by laboratories to inflate their performance figures; on the other hand it may be a reflection of a better quality of service since more patient information is being supplied per request.

The type of laboratory is found to be a source of cost heterogeneity, which matches previous literature (table 1). In our analysis, we were able to investigate this issue further. Laboratories situated in metropolitan areas are on average 9-17% more costly than laboratories in rural areas. The findings for urban-based laboratories are that on average they are 1-5% more costly than rural laboratories, likely owing to variation in the number and type of services provided, and higher disease burden associated with more densely populated geographical settings (though this finding is not statistically significant in all models estimated).

The foundation status of the host trust appears to be associated with a 4-10% reduction in operating costs for pathology laboratories. From the literature, profit incentives motivate hospitals to reduce costs to a greater extent than non-profit hospitals (Sloan, 2000), which is the aim of granting foundation status to a trust and should mean pathology services act commercially (Healthcare Commission, 2007).

Lastly, laboratories which provide teaching activities are found to have higher operating costs, 3-5%, to those which do not. This is in line with expectations, firstly because of the activity itself, but also because pathology services which are more specialised (and generally more expensive) tend to be associated with teaching activities, which may also be driving costs up (Department of Health, 2006). Moreover, this finding is in line with other health care studies (Gutacker et al., 2013).

The unobservable heterogeneity variable parameters (s(iii)) suggest that laboratories in London and the South are on average 7-15% and 1-5%, respectively, less expensive than laboratories from the North (the omitted dummy); and that operating costs of laboratories in the Midlands are on average 8-11% higher than those of laboratories in the North. From the literature, unobservable heterogeneity amongst these laboratories likely derives from information systems adoption, network activity and peer contact (Department of Health, 2006; Healthcare Commission, 2007; Eijkenaar, 2013). These features are more prevalent in London and the South and thus are likely driving this variation in costs.

Inefficiency Estimates

We find potential savings of £32.8m in our sample based on laboratories' efficiency estimates in their final year (average cost efficiency in final year = 0.86). We extrapolate to NHS pathology services (that is, all laboratories outside this sample and all other remaining pathology disciplines), giving an estimate of £390m per year of potential savings available to

contribute to the Nicholson Challenge. This is around double the savings estimate that was proposed in the grey literature based on a much smaller sample – extrapolated comparably - of around £250m (Department of Health, 2008). Recalling that this data is for biochemistry services - the most mechanised of the five major pathology disciplines - we envisage that our estimates may well underestimate the true level of inefficiency, since mechanised pathology services are more homogenous than other disciplines (Kiechle and Main, 2002). We thus conclude that this is more likely a minimum efficiency saving than a maximum, which underlines the importance of pathology services for policy makers if expenditure reduction is high on their agenda.

The average efficiency score over time is decreasing slightly. However, we find that individual etas imply that some laboratories are becoming more efficient over time, some are constant over time, and some are becoming less efficient over time (Fig.2); many of the laboratory-specific etas were found to be statistically significant. Information on the efficiency profiles of the individual laboratories is a powerful output of this type of top-down benchmarking as it indicates where further attention needs to be focused to drive out efficiency improvements. We do not report them here for confidentiality reasons.

Given that we have reduced efficiency over time and technical change (falling costs) as per the time trend coefficient in our preferred model (i.e. frontier shift), it is informative to compute the Total Factor Productivity (TFP) Index (Coelli et al., 2005) to give an overall account of pathology performance.

Year	Average cost efficiency	Cost efficiency index	Frontier Shift	Overall TFP Index	change TFP
2007	0.868	1	1	1	0
2008	0.839	0.967	1.014	0.981	-1.9%
2009	0.857	0.987	1.029	1.016	3.5%

2010	0.847	0.976	1.044	1.020	0.3%
2011	0.858	0.989	1.059	1.048	2.8%

Table 6: Total Factor Productivity pathology laboratories

As can be seen in table 6, the overall TFP for pathology is increasing over time, from 1.000 in 2007 to 1.048 in 2011. The annual change is positive for three of the years and negative for one year. Overall, TFP increases by 4.8% over the period of study. Thus, the small reduction in the efficiencies of laboratories away from the frontier is more than offset by the gains in costs by the efficient firms (the frontier shift), yielding the overall TFP increase.

Economies of scale in pathology

The cost elasticity estimates with respect to output indicate economies of scale properties in pathology production (Fig. 3). Further, MC is falling faster than AC (Figs 4 and 5), meaning that the elasticity is falling (Fig 3), so the extent of economies of scale is increasing as the scale of production increases. This is in line with predictions in the literature (table 1). This suggests that the growing formation of local pathology networks may help to lower costs for laboratories where production is pooled, which corresponds to pathology analysis elsewhere (Kiechle and Main, 2002). Encouragingly, this is being recognised by policy makers at the top level (Department of Health, 2011).

We note that the AC curve appears to be flattening towards the extreme of the sample. This, then, may be the production level at which economies of scale are exhausted. If this is the case, pooling several laboratories' production may result in diseconomies of scale setting in (each observation in this data is of a single laboratory's output). We note, however, that this cannot be concluded on this data and therefore leave this for future research.

VI. Conclusions

We have applied econometric efficiency estimation techniques to an under-researched area in health care literature: pathology. We have found, having controlled for cross-unit heterogeneity, 13% inefficiency in pathology services in the NHS in England. If this is indicative of NHS pathology as a whole, there could be £390m per year of available savings from pathology to contribute to the Nicholson Challenge of NHS efficiency savings.

We have found that laboratories' efficiency has, on average, decreased marginally over time. We have also found frontier shift which decreases costs over time. Overall, TFP for the laboratories in our sample has increased by around 5% between 2007 and 2011.

We have estimated the magnitudes of various drivers of laboratory costs which were identified from previous pathology studies. Some of these drivers have not previously been quantified (e.g. the costs of teaching or the effect of the host trust having foundation status). We have paid particular attention to the elasticity of cost with respect to output. We have found economies of scale, which is encouraging from a policy perspective because local networks are being formed in pathology services which increase the scale of production. We believe these findings are important to policy makers because it provides them with the evidence needed to make informed decisions on the allocation of resources and on the management of pathology services.

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