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Evaluating efficiency of English acute foundation trusts under system reform: a two-stage DEA approach

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Abstract
The English healthcare sector underwent extensive system reform over the period from 2010 to 2015, aimed principally at improving technical efficiency. This paper examines the effect of the reforms on foundation trusts in England with particular emphasis on technical efficiency. By employing data envelopment analysis (DEA) and a second-stage regression, we found evidence of an overall improvement in efficiency, notwithstanding some fluctuations. Specifically, we found that bed utilization had positive and statistically significant association with the efficiency of acute foundation trusts; suggesting that better management of patient flows and bed utilization might be expected to improve hospital efficiency. We also found evidence to suggest that efficiency might also be improved through better management of staff numbers, optimizing liquidity, and better utilization of assets such as buildings and information technology.

Keywords Efficiency · Data envelopment analysis (DEA) · Two-stage analysis · English foundation trusts · Hospital bed occupancy

1 Introduction

The National Health Service (NHS) England is the largest part of the United Kingdom (UK) healthcare system and employs around 1.2 million people to serve a population of 54.3 million citizens. Since its establishment in 1948, three pillar principles have guided health service delivery: (1) "meet the needs of everyone", (2) "free at the point of delivery", and (3) "based on clinical need, not ability to pay" (NHS Choice 2016). The main revenue source (98.8%) of the NHS budget is derived from taxation and National Insurance (The King's Fund 2017). As a result of the economic downturn in 2007 and 2008, and the subsequent period of austerity, the NHS England was exposed to considerable financial pressure thus prompting widespread reform.

Reform of the English healthcare system under the Health and Social Care Act 2012 was considered "the most wide-ranging and controversial restructure" (Powell 2016). As explained by Department of Health (2012b), the three main reasons for enacting the Act

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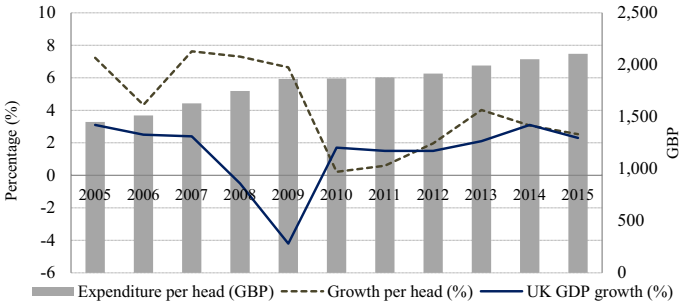


Fig. 1 Healthcare expenditure. *Source*: Authors' calculation using Public Expenditure Statistical Analyses 2010, 2013, and 2017 (HM Treasury 2017)

were to address the pressures arising from increased demand and treatment cost; to instigate improvements designed to avoid falling behind comparable countries; and to relieve pressure on public finances. On the basis of these three rationales, five major reforms were conducted: (1) formation of a new clinical commissioning group where clinicians' role would be enhanced; (2) providing greater choice to patients; (3) enabling providers to deliver quality services; (4) increasing accountability at both national and local level; and, (5) streamlining the arms-length healthcare bodies. A key driver of the policies was a belief that a quasi-market model and decentralization would yield greater efficiencies.

Alongside organizational changes, a striking feature during the period from 2010 to 2015 was the general atmosphere of budget austerity in the United Kingdom. As spending on health was the second largest component of the national budget—accounting for about 23% of all spending on public services in England over the 2009–2015 period (HM Treasury 2017)—savings from this area were deemed to be an important part of the national budget repair effort. Indeed, the savings target set for the NHS in England by 2014 was £15 to £20 billion (Roberts et al. 2012). Leading up to this time public health expenditure in real terms had grown at an average of 3.7%, but from 2009 to 2013 growth was reduced to just 0.7% per annum (Lanfond 2015). In per capita terms, the average rate of healthcare expenditure per person between 2004 and 2009 had grown at 6.6% per annum, but this rate was reduced to just 2.4% per annum for the period from 2010 to 2015 (see Fig. 1). Moreover, from 2011 onwards, the tariff (price paid to hospitals for services) was reduced in an attempt to realize the above savings target by 2014. The adjustment to the tariff was made in advance and was calculated by subtracting imposed efficiency dividends from the total increase attributable to pay and price inflation. As a result, providers faced a nett cut of 7.7% between 2010 and 2015; after accounting for the increases in the total efficiency of 23% and price inflation of 15.3% (see Table 1).

In addition to the policy-based changes, hospital services also encountered challenges such as increase in demand owing to growth in the size and aging of the population, increases in morbidity, and rising health costs for equipment and materials (Crawford and Stoye 2015; Licchetta and Stelmach 2016). Reactions by hospital managers to the changed budget and policy environment were varied but one clear response was to improve productivity (see Fig. 2). One way that this might occur would be, similar to other countries, for the number of staff in English hospitals to gradually increase but the total number of hospital beds (a frequently used indicator of hospital capacity) to decline. According to Baker (2017), "[s]ince 2011, the number of beds available

Table 1 Changes in the tariff (2009–2015). *Source*: Department of Health (2012a), Marshall et al. (2014) and Monitor (2015a, b)

Tariff year	Pay and price inflation (%)	Efficiency requirement (%)	Net tariff uplift (%)
2009–2010	4.7	−3.0	1.7
2010–2011	3.5	−3.5	0.0
2011–2012	2.5	−4.0	−1.5
2012–2013	2.2	−4.0	−1.8
2013–2014	2.7	−4.0	−1.3
2014–2015	2.5	−4.0	−1.5
2015–2016	1.9	−3.5	−1.6

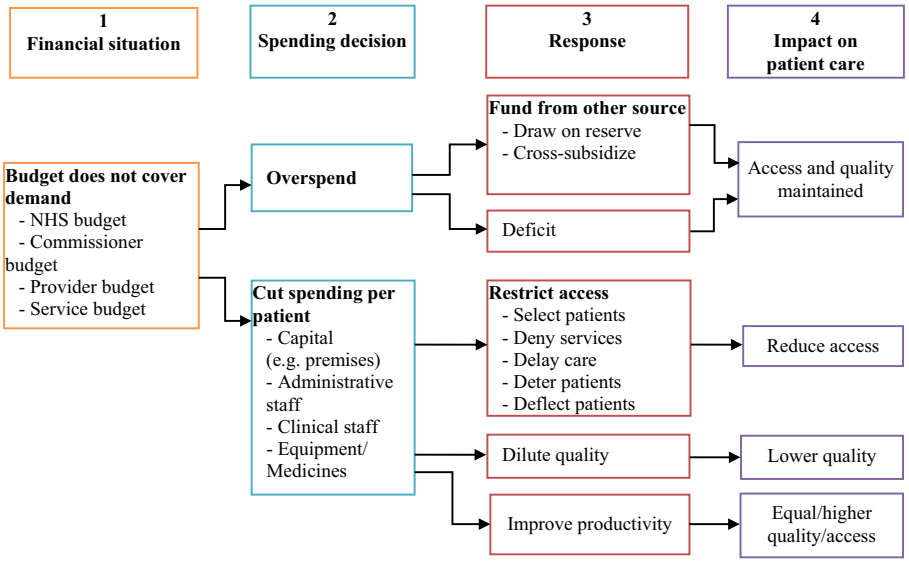


Fig. 2 Possible responses to the funding pressures. *Source*: Adapted from Robertson et al. (2017)

overnight has fallen by 7400 (a fall of 5.4%)", which seems to support this contention. Indeed, over the period 2009–2016, in comparison with other European Union (EU) countries, the UK had one of the lowest number of hospital beds per capita with around 3 per 1000 population, lower than the EU average level (5 beds) and far lower than the highest (Germany) which had around 8.3 beds per 1000 population (OECD 2017). The reduction in the number of beds might also be associated with a shorter length of patients' stay, which is typically considered as a sign of efficiency (OECD/EU 2016).

Thus, in responding to the economic and policy environment, hospitals were expected to use resources more efficiently to meet pressure from both increasing demand and higher quality expectations. This prompts at least three salient research questions. First, did the expected improvement to technical efficiency indicated by policy changes and budgetary constraints indeed occur over the period 2009–2016? Second, did reduction in beds contributed to any efficiency gained? Third, are there factors that explain any variability in efficiency across the hospitals which make up the foundation trusts in England?

To answer our three research questions we employed DEA on recent longitudinal data to estimate the technical efficiency of NHS foundation trusts. Although trusts and foundation trusts are both publicly owned hospitals, we focused on the latter as they make up about 66% of the total NHS hospitals and have more autonomy in governance and financial freedom than their peers. Foundation trusts were established as a new type of NHS hospital in 2004 and must meet strict criteria (e.g. well managed, legally constituted, financially viable) to attain the foundation trust status (Verzulli et al. 2018). Thus, foundation trusts and trusts are different in terms of financial and management perspectives and it might not be appropriate to combine them into one group to make a comparison. As of 31 March 2017, based on their principal services, 157 foundation trusts are categorized into five different types including acute (85), mental health (44) specialist (17), ambulance (5), and remaining community (6) (NHS Improvement 2017b).

DEA has been employed a number of times in relation to analyses of healthcare sectors, although there is a paucity of DEA research on UK hospitals (Valdmanis et al. 2016). Specifically, of 262 DEA papers reviewed over the period from 2005 to 2016, only one investigated UK hospitals (Kohl et al. 2018). We found that most DEA literature on the UK hospitals was published prior to 2006 (typically examining periods before 2000) and used crude output proxies (without adjusting for case-mix). Moreover, few of the extant works applied techniques such as second-stage analysis required to identify the determinants of efficiency (DEA measures efficiency, but second-stage analysis is important to identify the determinants of efficiency which is an entirely different matter). To remedy this gap, especially with reference to the absence of *UK* work on the determinants of efficiency, we used two-stage analysis with panel data regression to uncover factors associated with differences in efficiency across providers.

The remainder of the paper is organized as follows: In the next section, we summarize recent studies on evaluating hospital efficiency with DEA models. Following this, we explain our model specification and the reasons for selecting inputs, outputs, explanatory factors and the sources of data obtained. In the subsequent Result section, we present our findings and discuss the efficiency scores and the regression outcomes. We conclude with a brief discussion of the public policy findings suggested by our work.

2 Literature review

2.1 Application of DEA in measuring hospital efficiency

Efficiency is a key concept in economics, normally referring to the ability to maximize the outputs produced within a given level of inputs or alternatively minimize the uses of inputs to produce a chosen level of outputs. In the extant literature, there are two distinguished approaches to evaluate efficiency, stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The former is a parametric method developed by Aigner et al. (1977) which assumes that the residuals are decomposed into inefficiency and random errors and also that these two components are distributed differently. The latter is a deterministic method developed by Charnes et al. (1978) to measure the relative technical efficiency by using linear programming to identify an efficient frontier from the piece-wise linear combination of best practice units. Accordingly, in DEA inefficient units are enveloped by the efficiency frontier and the technical inefficiency of each unit is measured by the distance of each unit from the frontier (Coelli et al. 2005). There are inherent strengths and drawbacks

for each methodology. SFA accounts for noise and can be used to conduct tests of hypothesis but requires specification of a functional form and assumptions about the distribution of the inefficiency term (Coelli et al. 2005). On the other hand, DEA does not require a functional form or assumptions about the inefficiency distributional properties but is sometimes criticized for its deterministic nature and the lack of tests to verify the most appropriate model specification (Ozcan 2014).

Since the Charnes et al. (1978) constant returns to scale (CCR) model, later extended by Banker et al. (1984) to variable returns to scale (BCC), DEA has been increasingly applied which suggests its general acceptance by academics and practitioners alike, in a wide variety of situations (Chilingerian and Sherman 2011). Indeed, bibliographic collection of DEA literature over the period from 1978 to 2016 indicates a dramatic growth in publications which employ DEA techniques, of which healthcare is among the five most pervasive fields (Emrouznejad and Yang 2018). A possible reason for increasing application of DEA could be due to its ability to incorporate multiple inputs and outputs simultaneously with different unit measurements and without any requirement for prior weights or prices (Charnes et al. 1994).

Given that there are different types and levels of healthcare entities (e.g. primary care and secondary care; hospitals and nursing homes; specific services at hospitals), we emphasize DEA studies that examine hospital efficiency. In a summary of 317 publications up to mid-2006 that measure efficiency in healthcare, Hollingsworth (2008) indicated that a majority (80%) of research used DEA analysis and more than half of applications were with respect to hospitals. More specifically, Hollingsworth (2008) detailed that most research used inpatient days or discharges as hospital outputs while staff and capital employed were the main inputs. Similarly, O'Neill et al. (2008) systematically reviewed 79 studies on hospital efficiency using DEA published during the period from 1984 to 2004. They investigated different characteristics (e.g. types of model, choice of variables) to make a comparison between Europe and the US and found that European studies had a tendency to use panel data, and use a fewer number of inputs but a higher number of outputs. As an update to the research conducted by O'Neill et al. (2008), a comprehensive review of DEA literature on hospitals was conducted by Kohl et al. (2018) including 262 papers from 2005 to 2016, summarized below.

2.1.1 Research topics

Most of the DEA research (100 papers) were motivated by examining the association between efficiency and other salient factors (quality, ownership type, specialization, regulations) while others (99 papers) just simply conduct DEA, which can be classified as "pure DEA efficiency analysis". The next group (48 papers) focused on developing advanced and new DEA models (using the Malmquist index, comparing multifactor efficiency and nonradial super-efficiency). The last category comprised "surveys on the effects of reforms" (36 papers) which mainly made comparisons between efficiency before and after certain reforms to evaluate how the policy had influenced efficiency.

2.1.2 Additional techniques

DEA scores tended to be a starting point with extensive attention paid to further analysis, including Panel Data Analysis with Malmquist Index (47 publications) and Window Analysis (five papers); Bootstrapping was used in 20% of the papers. A particularly

important task from a public policy perspective is, as we have noted, to identify the determinants of efficiency.

DEA measures efficiency with variables employed to proxy inputs and outputs. However, to find the determinants of efficiency it is necessary to employ a different suite of variables which might be expected to explain the change in inputs and outputs (measured in DEA). Regression analysis is often employed for the purposes and was used in about 25–30% of the publications. However, the authors noted that no model was superior to or more reliable than the others. They suggested discussing theories and practical evidence with the stakeholders (hospital managers, policymakers, and economists) to find causes of inefficiency and enhance the robustness and the reliability of the results.

2.2 DEA literature on UK hospitals

Turning to studies on UK hospitals, we examined research up to two decades prior. Except for a few recent studies, it seems that most were conducted before 2006. Although NHS England is the largest constituent, serving more than 80% of the UK population, Scottish hospitals were examined more frequently. The purposes of these studies also varied, such as comparing the efficiency between small and large hospitals (Mccallion et al. 2000), evaluating the impacts of market reform on changes in efficiency or estimating efficiency changes over time (Ferrari 2006; Maniadakis and Thanassoulis 2000; Valdmanis et al. 2016). Other researchers investigated efficiency scores to verify the validity and potential application of DEA in the healthcare sector or comparing DEA results with other approaches (Hollingsworth and Parkin 2003; Jacobs 2001). Concerning the variables used to measure efficiency, beds, staff numbers, and costs were common inputs; whilst, inpatients and outpatients were the main outputs employed (see Table 2).

Using a different method, by combining different outputs and inputs with explicit weights and ordinary least square (OLS), Castelli et al. (2015) examined 166 English trusts and found that productivity was positively associated with higher bed occupancy and that foundation trusts tended to be less productive than their counterparts. Similarly, Aragon Aragon et al. (2017) explored factors influencing the productivity of English trusts in the period 2010–2012 and suggested that trusts were more productive than foundation trusts with diseconomies of scale in larger trusts.

2.3 Determinants of hospital technical efficiency

A number of existing studies (57 studies) in the healthcare sector have combined statistical methodologies and techniques with conventional DEA (Cantor and Poh 2018). These statistical methodologies included regression models, statistical tests, productivity change analyses, bootstrapping, and correlation analysis although regression analysis was the most common approach. The general objective was to help explain the variation in organizational performance.

Reviewing several recent papers, where DEA has been used to measure efficiency and second-stage analysis have been employed to find the determinants of efficiency, it appears that external and internal drivers can be classified into socio-economic factors, patient and hospital characteristics, and economies of scale and scope.

Table 2 DEA literature on the UK hospitals

References	Sample	Method	Input	Output	Finding
1. Mccallion et al. (2000)	23 Northern Ireland hospitals (1986–1992)	DEA window Analysis and Malmquist Index	Nursing Administration Ancillary Specialists Beds	General surgery General medicine Maternity A&E	For smaller hospitals, an increase in technical change offset the decline in efficiency change which is due to a decrease in scale efficiency Larger hospitals are more efficient in providing healthcare services
2. Maniadakis and Thanassoulis (2000)	75 Scottish acute hospital (1991–1995)	Malmquist Index	Doctors (whole time equivalent—WTE) Nurses (WTE) Other personnel (WTE) Number of hospital beds Cubic meters of hospital buildings (per 100)	Accident and Emergency attendances Inpatients (case-mix) Day cases (case-mix) Outpatients (case-mix)	Given the moderate improvement in productivity was achieved, there still scope for further gains Productivity change could not attribute to the internal market reform Productivity gained mainly stemmed from the allocative efficiency
3. Ferrari (2006)	53 acute Scottish hospitals (1991–1996)	Malmquist Index	Total capital charges Medical staff (Full Time Equivalent—FTE) Nursing staff (FTE) Other staff (FTE) Total number of beds	Inpatients, surgery Inpatients, medical Inpatients, others; Outpatients, day cases, and day patients	Frontier shift and technical efficiency changed in an opposite direction and unclear trend Overall, technical efficiency reduces by one percent suggesting that the introduction of competition for hospital services had no significant effect on efficiency

Table 2 (continued)

References	Sample	Method	Input	Output	Finding
4. Valdmanis et al. (2016)	43 general acute Scottish hospitals (2003–2007)	Malmquist Index (with bootstrap procedure) and OLS time-series for trend analysis	Staffed beds Doctors (physicians and dentists) Nurses (including nurse trainee) Other labors	Inpatients (case-mix adjusted) Outpatients and short stay patients	The authors could not found consistent patterns in technical change and efficiency change A continuous decline in technical change implying that technical changes in previous periods are negatively associated with changes in the subsequent period

2.3.1 Socio-economic factors

These included population density, population over 65,youth-unemployment, full-time employment, elderly dependency rate, education, income (household income, income inequality), hospital density, expenditure on health, hospital (private, public), gross domestic product, life expectancy, infant mortality, and competition.

In their investigation of the hospital sector in OECD countries, Varabyova and Schreyögg (2013) found that countries with good health outcomes, higher income inequality and a longer average length of stay tend to be technically inefficient while countries with higher health expenditures per capita were positively correlated with hospital efficiency. Similarly, Kaya Samut and Cafrı (2016) suggest that both GDP and educational attainment have positive links with hospital efficiency. In an Italian hospitals' context, Matranga et al. (2014) found that while unemployment rates in young males and the average length of stay had a negative impact on hospital efficiency, improvement in socio-economic conditions could have a positive impact.

2.3.2 Patient characteristics

These included age structure (older patients), percentage of Medicare and Medicaid patients, length of stay, and bed occupancy ratio.

Czypionka et al. (2013) found that patients aged over 80 years have a negative influence on efficiency in Austrian acute hospitals. An inverse relationship between inpatient age and hospital efficiency was also observed for Canadian acute care hospitals (Fixler et al. 2014). For a specific group of US hospitals, Chou et al. (2012) and Nedelea and Fannin (2013) found that the percent of Medicaid admissions had a positive and significant effect on technical efficiency. A positive association between occupancy ratio and efficiency were indicated in the cases of Greek hospitals (Kounetas and Papathanassopoulos 2013), Austrian hospitals (Czypionka et al. 2013), and Canadian acute hospitals (Fixler et al. 2014).

2.3.3 Hospital characteristics

These included size/capacity (based on the number of beds), region (rural, urban), ownership (public, private), for-profit and non-profit hospital, teaching and non-teaching, advanced technology adoption, numbers of operation years, degree of specialization (Herfindahl–Hirschman Index).

When comparing hospitals with different ownership types, public hospitals were negatively correlated with efficiency, and private hospitals had a positive association (Czypionka et al. 2013; Kaya Samut and Cafrı 2016).

2.3.4 Economies of scale and scope

Giancotti et al. (2017) speculated that hospitals' scale and scope might be expected to have a considerable effect on efficiency. In a review of studies over 45 years (1969–2014) investigating the optimal size of hospitals, they found that while hospitals with 200–300 beds reaped economies of scale, diseconomies of scale occurred above 600 beds. Regarding economies of scope, a study of Portuguese hospitals by Ferreira

et al. (2018) suggests that, generally, hospitals can exploit economies of scope, however, this is unlikely to happen in larger hospitals (those with more than 6000 discharges and/or 7500 medical appointments).

Generally, DEA and its integrated models have been a preferred method in measuring the efficiency of hospitals and explaining the variation in efficiency scores. Also, it should be noted that the number of inputs and outputs, as well as explanatory factors, varies by study depending on research aim and data availability. However, given the wide application in many countries, it appears surprising that there is a scarcity of recent DEA applications on measuring the efficiency of English hospitals.

3 Models selected and data

3.1 DEA model specification

DEA employs linear programming techniques to calculate relative technical efficiency scores by optimizing the ratio of weighted sum of outputs to weighted sum of inputs when weights are unknown. The CCR and BCC DEA models involve choices around "orientation" and "returns to scale". O'Neill et al. (2008) argue that most studies use an input-oriented model since "hospital managers and policy-makers generally have more control over their inputs than their outputs, and, in a majority of countries, the emphasis is on controlling costs rather than increasing demand for healthcare". Over the period examined, English hospitals were under severe funding pressure with value for money being a key concern, making it likely that managers were motivated to use resources more efficiently to provide a given volume of services. Therefore, an input-oriented model was selected for this study.

The CCR model assumes a constant return to scale (CRS), suggesting that inputs and outputs increase or decrease proportionally or that all DMUs operate at an optimal scale. By contrast, the BCC model relaxes this assumption, allowing for variable returns to scale (VRS) which implies the existence of economies or diseconomies of scale. In the context of healthcare services, hospitals might not always perform at an efficient scale due to the restraints on available resources, legal framework and the market characteristics (Jacobs et al. 2006). More particularly, Kirigia and Asbu (2013) suggest that increasing returns to scale happen when resources are not completely divisible (e.g. medical equipment, operating theatre). On the other hand, a further increase beyond the optimal level might reduce efficiency in management due to growing complexity, difficulties in communication and distraction executing organizational strategies (i.e. decreasing returns to scale). It is expected that hospitals could exhibit variable returns to scale, however, Chilingerian and Sherman (2011) argue that hospitals are expected to operate at constant returns to scale. More than 50% of studies used CRS in the period from 1984 to 2004 (O'Neill et al. 2008), though recent studies tend to use the VRS model. Since no model has been proven to be superior, in the first stage, we will estimate efficiency under both CRS and VRS assumptions. However, in the two-stage analysis, as some of the explanatory variables explicitly reflect hospital size, scores under CRS have been employed to avoiding potential bias.

Thus, both CRS and VRS DEA modeling (input-oriented) are used in this study to estimate the efficiency of the foundation trusts. However, unlike cross-section DEA analysis, as our study uses longitudinal data (8 years), it is unsuitable to simply compare normal

DEA scores between different time periods because they are calculated on different reference groups. Therefore we adopt global inter-temporal DEA as a measure to investigate the changes in technical efficiency. The notion of this method is that all data across time are first pooled into a single DEA analysis, and then the DEA scores are regrouped in each year. However, the DEA scores used in the two-stage analysis (regression model) are calculated for each year separately to avoid being serially correlated.

Selecting inputs and outputs is an important task in specifying the DEA model. Based on prior literature, inputs are categorized into three groups—capital investment, labor, and other operating expenses, while patient numbers are the main constituents of the outputs (O'Neill et al. 2008; Ozcan 2014). Over the period examined from 2005 to 2016, the most popular inputs used by studies were beds, numbers and type of staff (medical staff, nurses, and nonmedical staff), supplies, equipment, and infrastructure, whilst outpatients, inpatients, and surgery were the most frequent outputs (Kohl et al. 2018), although this varied a little according to the authors' research questions and data availability. In relation to variable selection, Barnum et al. (2011) contend that DEA scores might be incorrect when using non-substitutable inputs and non-substitutable outputs. Therefore, the authors proposed solutions such as using prices or reasonable weights to aggregate non-substitutable variables or incorporating just one of the non-substitutable variables as a proxy for input and output, respectively. However, such measures might be inapplicable for use in this study given the absence of available prices, the arbitrary weights chosen and the inability for a proxy to capture the multiple aspects of hospital production. In addition, the exclusion of high correlation inputs or outputs might also distort the efficiency estimated (Dyson et al. 2001).

Accordingly, in this study, seven inputs were used including the number of available beds (a proxy for capital investment), staff numbers, assigned to five distinct categories (representing labor resources; see Table 3), and other operating expenses. With respect to the output side, since each patient has a different magnitude of complexity and requires different resources, "crude outputs" might not account for the patient heterogeneity (a heart transplant cannot reasonably be counted the same as a broken leg). Therefore, we used case-weighted volumes for outputs. Using reference cost data (NHS Improvement 2017a), we classified hospital activities into four main categories, namely, inpatients, outpatients, emergency and other services. Each activity is associated with HRGs (Healthcare Resource Group) with information about volumes and national average unit cost. The case-weighted volume for each output category in a hospital was calculated using the following formula:

$$\text{Case-weighted volume} = \frac{\sum_{j=1}^{n} x_{jh} c_j}{\bar{c}}$$

where x_{jh} is the amount of activity or HRG $j = 1 \ldots n$ at hospital h with $h = 1 \ldots m$, c_j is the mean unit cost of each HRG or activity. $\bar{c}$ is the average cost of all HRGs at the hospitals studied and calculated by the formula: $\bar{c} = \frac{\sum_{h=1}^{m} \sum_{j=1}^{n} x_{jh} c_j}{\sum_{h=1}^{m} \sum_{j=1}^{n} x_{jh}}$.

Relevant data were retrieved from official databases, including Monitor (2017), NHS Digital (2017) and NHS England (2017a). Since some foundation trusts had been recently transformed and some lacked sufficient data over the study period, 116 out of 157 foundation trusts were collected (70 acute, 32 mental health, and 14 specialist). However, these

Table 3 Statistical descriptions for variables used in the DEA model

Variable	Description	Mean	SD
Inputs			
Number of beds	The average number of beds available at hospitals	767	305
Medical staff	The number of full-time equivalent (FTE) medical staff	584	329
Nurses, health visitors, and midwives	The number of nurses, health visitors, and midwives (FTE)	1494	766
Scientific, therapeutic and technical staff	The number of scientific, therapeutic and technical staff (FTE)	625	363
Support for clinical staff	The number of support to clinical staff (FTE)	1366	640
NHS infrastructure support and others	The number of NHS infrastructure support and others (FTE)	754	403
Operating expenses (£1000)	Other operating costs excluding staff payroll, depreciation and amortization expenses, and impairments (adjusted for inflation)	132,002	94,851
Outputs			
Inpatients	The volume of activities related to patients admitted and treated while staying inside a hospital (elective, non-elective, excess bed days, critical care)	157,550	76,016
Emergency	The volume of activities in accident and emergency unit	110,092	44,956
Outpatients	Volume of outpatient services	526,910	266,144
Other services	Volume of other hospital activities, such as other acute services, community services, etc	2,644,675	1,635,744

three types of foundation trusts are likely to have different production functions and characteristics resulting in problems with the homogeneity assumption if they were aggregated into a single sample. Given that the numbers of acute trusts met the rule of thumb[1] for sample size in carrying out DEA analysis, the mental health and specialist trusts were excluded from the research. Moreover, because we were dealing with a sample rather than a census of foundation trust data, we bootstrapped our results with 1000 replications. Descriptive statistics of inputs and outputs are given in Table 3.

3.2 Regression model

Although DEA allows us to identify efficient and inefficient hospitals, it cannot provide insights on the determinants of the efficiency scores which is likely to be a major concern for policymakers and hospital managers. Moreover, while hospitals under evaluation are assumed, by DEA, to operate under similar environmental conditions, this assumption is not always applicable in reality. Indeed, various factors might affect hospital performance (e.g. patient characteristics, economic conditions, quality of resources), hence failure to account for these differences might lead to biased judgments (Jacobs et al. 2006). Therefore, regression analysis has been extensively employed in the literature to identify an association between efficiency and possible explanatory factors (Cantor and Poh 2018), although such analysis has rarely been conducted in recent literature on UK hospitals. We concede that two-stage analysis is an exploratory approach rather than being based closely on theory, and it is challenging to test whether environmental variables are independent of the production function, however, it is one of the two important evolutions of DEA which attempt to identify determinants of efficiency (Førsund 2018). It thus seems an important approach to take in our work. Despite the second stage regressions being widely utilized, there has been little consensus in choosing the type of regression model for two-stage analysis. Banker and Natarajan (2008, p. 57) argue that "two-stage DEA-based procedures with ordinary least square (OLS), maximum likelihood (ML), or even Tobit estimation in the second stage significantly outperform the parametric methods". Similarly, while Hoff (2007) concluded that either the Tobit model or OLS is acceptable McDonald (2009) argue that since DEA scores are fractional data Tobit is not suitable and OLS should be the preferred method. Following a different approach, Simar and Wilson (2007, 2011) developed a bootstrapped truncated regression model, pointing out that the method outperforms the Tobit model and criticized the use of OLS for its dependence on restrictive assumptions.

Since the debate is ongoing, we have followed Lovell et al. (1994) who used super efficiency scores as the dependent variable to remove the upper bound problem (and hence the justification for Tobit regression modeling). Accordingly, we use a standard fixed effects panel data regression for the second stage analysis.[2] Our focus in doing so was to investigate how hospital characteristics, patient characteristics, asset management, and staff satisfaction might

[1] In order to have adequate numbers of degrees of freedom (adequate discriminatory power for the DEA model), the "n" (number of DMUs) should exceed the number of inputs (m) and outputs (s) by several times. More specifically, a suggested rule of thumb formula is that that "n" should be greater than max {m*s, 3* (m+s)}.

[2] By way of a robustness check, we did also run regressions employing Tobit random effects, and OLS (with year dummies) and found that the results were quite similar. These results are available from the corresponding author.

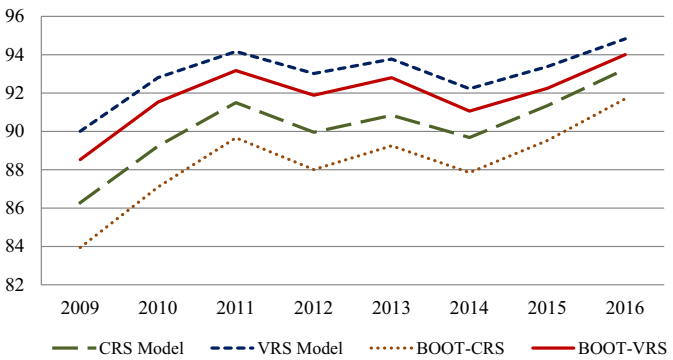
Table 4 Statistical description of variables used in the regression model

Variable	Description	Mean	Median	SD
EFF	The score(ln) using the super-efficiency model whereby the scores for efficient hospitals can exceed 100%	4.66	4.62	0.19
LN(SOPE)	The range of services that a hospital provides based on the numbers of the main groups in the Health Resource Groups (HRGs)—subchapters with three first code characters	5.19	5.14	0.20
OCCU	The bed occupancy defined as the rate of occupied beds over available beds.	0.87	0.87	0.06
OLD	The proportion of the patients over 60 years divided by total admissions	0.56	0.56	0.11
LN(EQUIP)	The average net value of medical equipment (including plant and machinery), divided by the total volumes of services provided (unadjusted for case-mix)	− 5.43	− 5.44	0.64
LN(BUILD)	The average net value of accommodation (building plus dwelling) divided by the total volumes of services provided (unadjusted for case-mix)	− 3.13	− 3.24	0.62
LN(INFOR)	The average net value of information technology divided by the total volumes of services provided (unadjusted for case-mix)	− 6.88	− 6.87	0.72
LN(INVENT)	The net value of inventory divided by total volumes of services provided (unadjusted for case-mix)	− 6.58	− 6.64	0.70
LN(RECEIV)	The net value of trade receivable divided by total volumes of services provided (unadjusted for case-mix)	− 5.35	− 5.49	0.74
SATISFA	The staff satisfaction defined as the scores given by staff from the annual survey ranging from 0 (lowest) to 5 (highest).	3.67	3.65	0.20
LIQUID	$LIQUID = \frac{\text{Net liquid resources}}{\text{Operating expenses (excluding Depreciation)}} * 365$ Net liquid resources = [Current assets (excluding Inventories, Derivative related assets, Available/held for sale assets and Charitable funds assets)]–[Current liabilities (excluding Charitable funds liabilities)]	3.46	1.10	19.4

Some data use the same sources as DEA model; the satisfaction scores sourced from National NHS Staff Survey Co-ordination Centre (2018)

Table 5 DEA scores

	2009	2010	2011	2012	2013	2014	2015	2016
CRS model								
Average	86.28	89.23	91.50	89.96	90.84	89.68	91.34	93.25
Median	86.60	88.92	91.12	91.06	92.13	90.06	92.34	94.09
Min	66.51	72.41	75.65	66.3	65.53	68.03	67.98	69.66
Max	100	100	100	100	100	100	100	100
SD	7.16	6.49	6.83	7.11	7.44	6.71	6.57	6.65
Number efficient units	4	4	11	8	11	5	4	19
VRS model								
Average	90.01	92.81	94.17	93.02	93.77	92.23	93.38	94.83
Median	90.25	93.22	96.19	94.37	95.03	93.40	94.57	98.14
Min	68.52	74.56	79.19	70.22	67.96	68.03	70.09	70.28
Max	100	100	100	100	100	100	100	100
SD	7.54	5.99	6.08	6.7	6.66	6.42	6.26	6.39
Number efficient units	10	12	20	17	21	12	12	29



Note: CRS – Constant returns to scale; VRS – Variable returns to scale; BOOT – Bootstrapped.

Fig. 3 The efficiency trend 2009–2016

be associated with hospital efficiency. The specification for the regression model is given by the following equation:

$$\begin{aligned} EFF_{i,t} = {} & \beta_0 + \beta_1 LN\left(SCOPE_{i,t}\right) + \beta_2 OCCU_{i,t} + \beta_3 OLD_{i,t} \\ & + \beta_4 LN\left(EQUIP_{i,t}\right) + \beta_5 LN\left(BUILD_{i,t}\right) \\ & + \beta_6 LN\left(INFOR_{i,t}\right) + \beta_7 LN\left(INVENT_{i,t}\right) \\ & + \beta_8 LN\left(RECEIV_{i,t}\right) + \beta_9 LN\left(SATISFA_{i,t}\right) \\ & + \beta_{10} LIQUID_{i,t} + \varepsilon_{i,t} \end{aligned}$$

Table 6 The average growth of inputs and outputs (%)

	Beds	Staff	Operating expenses	Inpatients	Emergency	Outpatients	Others
2009–2011	−2.42	1.03	5.59	2.20	7.97	3.02	11.67
2012–2014	0.40	3.43	4.30	1.77	3.01	5.13	−0.57
2015–2016	0.28	−0.43	3.44	3.88	2.26	3.38	7.35
Average	−0.49	2.74	4.73	2.43	4.39	3.66	5.66

Table 7 Growth rates of employees

	Medical staff (12%)	Nurses and health visitors; Midwives (31%)	Scientific, therapeutic & technical staff (13%)	Support to clinical staff (28%)	NHS infrastructure support and others (16%)
2009–2011	1.73	0.91	3.08	1.01	−0.86
2012–2014	4.37	3.12	2.28	4.78	1.86
2015–2016	0.71	−2.14	−3.12	1.18	1.35
Average	2.83	2.37	2.72	3.59	1.91

The number in () is the average proportion of each staff type

Where: The set of β_k (k = 1,…, 10) denote the parameters estimated from the panel regression model while $\varepsilon_{i,t}$ represent the error term and $E(\varepsilon_{i,t}) \sim N(0, \sigma^2)$. Descriptive statistics for variables are provided in Table 4.

4 Results and discussion

4.1 DEA scores

Results from the first stage are reported in Table 5 and graphed in Fig. 3.

Over the period from 2009 to 2016, the overall efficiency of English acute foundation trusts increased in what appears to three phases: the first (2009–2011) mean scores increased, falling back slightly in the second phase (2012–2014) and then increasing again in 2015 and 2016. The efficiency trends are similar under both CRS and the VRS model. However, the VRS technical efficiency scores are constantly higher (as expected) than those of CRS confirming the existence of scale inefficiency. The VRS model also indicates that, on average, a large proportion of hospitals (76%) were operating at increasing returns to scale, 24% were at a constant return to scale and none experienced decreasing returns to scale.

Examining the input and output data, it appears that the utilization of resources and responses to national policies could have been the main factors explaining the efficiency trends. Generally, over the period 2009–2016, input growth seemed to be lower than the respective growth in outputs (see Table 6). Specifically, a reduced number of beds and staff were the main factors contributing to the improved efficiency of the foundation trusts (over the whole period as well as for each specific phase). In both 2009–2011 and

Table 8 Length of stay (days). *Sources*: Authors' calculation and summarizing based on annual Hospital Episode Statistics (HES) published by NHS Digital

	2009	2010	2011	2012	2013	2014	2015	2016
Investigated foundation trusts	4.42	4.26	4.21	4.25	4.25	4.22	4.15	4.17
Overall England	5.60	5.50	5.30	5.20	5.10	5.00	4.93	4.91

2015–2016 when efficiency significantly improved growth in the number of employees and beds was much lower than in 2012–2014. Similarly, growth of inpatients, emergency, and other services in phases 1 and 3 were generally higher than phase 2.

Nurses, health visitors, midwives, and support to clinical staff made up almost 60% of the numbers of total staff (see Table 7). During the period from 2010 to 2014, while infrastructure related staff declined (around 20,000 FTEs), clinical and support to clinical staff increased (around 31,000 FTEs) which rebalanced the NHS staff structure toward clinical staff (Applyby et al. 2015). A contributing factor may have been pressure arising from the Mid-Staffordshire scandal,[3] which might have encouraged hospital management to recruit more staff to secure acceptable service standards (Applyby et al. 2015; Powell and Mannion 2016). In addition, increases in the number of hospital employees may have resulted from the Transforming Community Service program over 2010–2012 when Primary Care Trusts (PCTs) were required to separate commissioning functions and community services (Department of Health 2010). As a consequence, some acute foundation trusts took over staff and assets when the provider arms were absorbed by the foundation trusts (Clover 2011). Thus, the growth in staff numbers was the likely cause of the fluctuations in technical efficiency during the period 2012–2014.

In addition, NHS England during this period reduced the number of beds and increased the number of patients. Thus, greater utilization of beds to meet rising demand is likely to have been an important driving factor for efficiency improvement. As can be seen in Table 6, bed numbers slightly decreased or at least remained stable whilst output volumes constantly increased. Enhancing day surgery and shifting traditional treatment to community care might have helped to free up a number of beds (Baker 2017). In addition, length of stay (LOS) declined consistently during the period 2009–2016 (Table 8).

The reduction in LOS could have been a response to meet the growing demand within the constraints of limited capacity where each hospital was required to actively respond to the introduction of the Referral to Treatment waiting time standard[4] (NHS England 2017b). While the percentage of incomplete pathways within 18 weeks was around 90% before 2013, this indicator had increased to about 93% during 2013–2016. Some hospitals might have responded to the requirements by putting a higher priority on less complex patients as they require a shorter time to treat (Morris 2018), but others might have dealt with the issue by reducing patients' length of stay (Lewis and Edwards 2015; Nuffieldtrust

[3] Mid-Staffordshire failure (dated back to late 2000s) related to unacceptable poor standards and high mortality rate at Stafford hospital which is considered to be the most notorious stigma in the NHS England history.

[4] Patients should be treated either as an inpatient or as an outpatient within 18 weeks of the referral. In 2013 additional target set was that no-one has to wait for more than 52 weeks to be treated. In June 2015, the admitted (90%) and non-admitted (95%) metrics were terminated, the only measure left is incomplete pathway standard.

Table 9 Regression results

Variables	Fixed effect model	Standardized model
LN(SCOPE)	−0.139***	−0.022*
	(0.045)	(0.013)
OCCU	0.476***	0.025***
	(0.155)	(0.009)
OLD	−0.442**	−0.062**
	(0.213)	(0.024)
LN(EQUIP)	−0.016	−0.007
	(0.036)	(0.024)
LN(BUILD)	−0.101***	−0.058***
	(0.035)	(0.022)
LN(INFOR)	0.022	0.021*
	(0.015)	(0.011)
LN(INVENT)	0.047	0.037
	(0.035)	(0.025)
LN(RECEIV)	0.012	0.004
	(0.023)	(0.019)
SATISFA	0.073	0.005
	(0.053)	(0.010)
LIQUID	−0.004***	−0.074***
	(0.001)	(0.010)
Constant	5.085***	4.657***
	(0.291)	(0.005)
Observations	483	483
R-squared	0.218	0.182
Number of hospitals	69	69

Standard errors in parentheses

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

2014). Indeed, a variety of measures have certainly been deployed for this purpose, including the provision of recovery care at home through the use of "virtual wards"; improved pathways for frail patients; additional supply of seven-day support for discharged patients; and special arrangement for seniors to make early decisions about the treatments. Through these innovations, NHS hospitals shortened patients LOS, and avoided financial penalties, in order to cope with a limited number of beds.

4.2 Regression results

In the second stage, we identify the determinants of efficiency which we previously measured using DEA for English acute foundation trusts. Different panel data models (Fixed effects and Random effects) were estimated and since the Hausman test result did not support that the composite error term was uncorrelated with the explanatory variable ($Prob>chi2=0.000$), we elected to adopt the Fixed effects model. In order to compare both the significance, and the relative size (and hence importance) of the explanatory

Table 10 Variance inflation factor (VIF)

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LN(SCOPE)	1.39	1.18	0.72	0.28
OCCU	1.13	1.07	0.88	0.12
OLD	1.36	1.16	0.74	0.26
LN(EQUIP)	3.82	1.96	0.26	0.74
LN(BUILD)	4.08	2.02	0.25	0.75
LN(INFOR)	1.70	1.30	0.59	0.41
LN(INVENT)	3.57	1.89	0.28	0.72
LN(RECEIV)	4.94	2.22	0.20	0.80
SATISFA	1.60	1.26	0.63	0.37
LIQUID	1.19	1.09	0.84	0.16
Mean VIF	2.48			

variables, suggested by the extant literature, both the standard model and normalized fixed-effects model (using the standardized values of the original regressors) were estimated.

The results of both regression models are provided in Table 9. We also conducted a commonly employed multicollinearity test and found that the mean variable inflationary factor (VIF) was 2.48 (none of the VIFs is larger than 5), suggesting that the regression model does not suffer from multicollinearity problem (Berta et al. 2010; Ding 2014; Dong 2016; Jindal et al. 2018; Şamiloğlu and Akgün 2016) (see Table 10).

The results from our regressions suggest that scope, bed occupancy rate, proportion of elderly patients, effect of accommodation, information technology and liquidity are all statistically significant determinants of relative technical efficiency.

Economies of scope arise when a hospital could make the cost lower through diversification of the types of services provided by taking advantage of sharing the resources used. However, it is important to remain cognizant that diseconomies of scope may also arise—that is, that relative greater diversification can cause inefficiency. The negative coefficient in our analysis supports the (latter) case that hospitals with more types of services tend to have lower efficiency. As explained by the Monitor (2014) expanding the scope of services might, in fact, have deleterious effects on financial status, since additional income might be insufficient to offset the additional costs incurred.

A higher bed occupancy rate is generally assumed to be positively associated with efficiency. A theoretical and simple threshold of hospital occupancy rate is around 85%, at which point access block, waiting lists or seasonal bed crises can still be mitigated (Bain 2010; Jones 2001, 2011; Keegan 2010). The average occupancy rate of these acute foundation trusts over 2009–2015 was at about 87%, higher than the recommended cut off ratio but still lower than the maximum rate (90%) proposed by National Institute for Health and Care Excellence (NICE 2017). Thus, a strong positive association between occupancy rate and hospital efficiency confirms the importance of this variable in the modelling.

Older patients normally require more intensive medical examinations and elicit higher resource consumption.[5] Thus, a higher proportion of older patients might be expected to inversely affect efficiency. The average percentage of older patients (aged 60^{+}) in the acute

[5] In examining expenditure characteristics of England public hospitals, Kelly et al. (2016) point out that costs accelerate when the patients' age increase.

foundation trust between 2009 and 2015 was 56%. Although one might expect that the costs incurred when treating old patients should be covered by the tariff, it is, however, reasonable to argue that the fixed tariff might only partially adjust for the variations in the patient ages and the inefficiency still occurs when the proportion of old patients increase. Thus, the negative coefficient in our empirical estimations confirms that a higher proportion of elderly patients tends to have a deleterious effect on relative technical efficiency.

The effect of accommodation (buildings and dwellings) suggests that with the same amount of assets, a hospital with a higher volume of services delivered yields higher efficiency. It is important to note that the nett building value excludes depreciation, but includes capitalization for new construction and work which extends the functionality or useful life of the asset (as well as other 'accounting treatments'). Therefore, accomodation is unlikely to be correlated with depreciation. Moreover, as indicated by Lord Carter of Coles (2016), inefficiency related to accommodation in acute trusts stems mainly from underutilization or inappropriately used buildings for non-clinical and unproductive purposes. Indeed, space that was not occupied by patients varied significantly across trusts, ranging from 12 to 69%. Other examples of wasted resources that might affect efficiency include buildings built in inappropriate locations, outdated buildings (due to changes in treatment), and over-specified inflexible spaces (Edwards 2011). Since accommodation accounts for the majority of total fixed assets (74%) and given their substantial operating and maintenance costs, our finding implies that there are significant opportunities to improve efficiency through better use of these facilities.

The positive effect of information technology (IT; in the standardized model only) implies that investment in IT improves hospital efficiency. A large part of IT relates to the digitalization of the health system which aims at better services and lower cost. In fact, in an attempt to improve its efficiency, since 2002 NHS England has deployed the National Programme for Information Technology (NPfIT) which represents a £12.4 billion investment. Although terminated in 2011, it was able to achieve "single national patient identifier, infrastructure to provide core services, and national electronic prescription" (Wachter et al. 2016). It should be noted that NPfIT goals still remain and that the NHS continues to pursue digitization in secondary care (NHS England 2014).

Liquidity is one of the financial indicators utilized by the Monitor to evaluate financial risk (a higher metric means lower risk) of each hospital. However, the regression result suggests that liquidity is negatively associated with hospital efficiency. The relationship between liquidity and profitability in the business sector has been examined with mixed evidence of both positive and negative correlation between these two factors (Şamiloğlu and Akgün 2016; Umobong 2015). Although it might not be strictly appropriate to apply business concepts to hospitals (and also because liquidity is often measured differently), foundation trusts are expected to generate a surplus which they are entitled to reinvest in services from retained earnings. Thus, when foundation trusts hold large nett working capital to enhance solvency, there might be a trade-off relationship between liquidity and profitability, as well as efficiency.

Notably, all of the coefficients in the standardized model are relatively small which suggests that public policy interventions designed to address the determinants can be expected to have relatively marginal effects on overall relative technical efficiency. When comparing the magnitude of potential impacts, the standardized coefficients suggest that liquidity and proportion of old patients have the greatest effects, followed by accommodation, occupancy rate, and information technology. Public policy might, therefore, be prioritized first for the variable that is most amenable to change and likely to produce the greatest effect such as liquidity, accommodation, and occupancy.

For the variables that were not statistically significant the signs of the coefficients were broadly in line with expectations. In order to meet the treatment timeline targets, NHS England invested more on medical equipment and as a result, there was an increase in the number of MRI units and CT scanners (Cylus et al. 2015). However, new medical technologies are generally expensive and may not be the most efficient use of capital (Sorenson et al. 2013). Therefore, hospitals with a higher value of medical equipment might be less efficient (hence the negative coefficient in Table 9). The positive association for inventory was in line with the argument that "hospitals are likely to overstock to ensure high patient safety and bring the costs down when contracts with suppliers are negotiated" (Gebicki et al. 2014, p. 219). Similarly, the coefficient for receivables was consonant with our expectations—generally, shorter receivable periods might be expected to improve profitability, however, a strict policy to promptly collect can divert resources from more efficient uses (Şamiloğlu and Akgün 2016). Finally, the positive coefficient for staff satisfaction was also in line with our expectations—staff are likely to be more dedicated and enthusiastic (e.g. lower absenteeism) when they have higher satisfaction (consistent with previous studies; Powell et al. 2014).

5 Conclusion and policy implications

Our objective was to extend the literature on UK hospitals conducted prior to 2006 through an evaluation of how the technical efficiency of English foundation trusts changed over 2009–2016 under conditions of budget austerity and restructuring and examine the causes of variation in efficiency across hospitals.

Overall, technical efficiency of the acute foundation trusts investigated clearly improved, albeit with fluctuations over the period 2012–2014 period. Through our data analysis and other evidence, we have suggested that the efficiency gains appear to mainly result from bed optimization and initiatives to reduce the length of stay. We also found evidence to support the contention of scale economies given that most of the hospitals were operating at the increasing returns to scale.

The results obtained from the two-stage analysis with regard to determinants of efficiency seem to be consistent with findings in the prior literature: Wider scope and a higher proportion of old patients reduce efficiency, while higher bed occupation rates increase efficiency. Although hospitals have less discretion in choosing what services to provide and thus have a lower degree of control over these factors, utilizing tools such as Service Line Report (SLR) and Patient Level Costing (PLICS) to identify the least efficient areas and to balance services provided seem to have potential to mitigate negative impacts associated with scope.

As the number of older patients is likely to continue to trend upwards, optimization of hospital beds will also be an essential means through which to improve efficiency. Better management of length of stay (LOS), especially adequate management of older patients LOS will benefit not only hospitals but also the patients themselves. In this regard, as a policymaker, the NHS Improvement has an important role to disseminate successful initiatives and good practice (in optimizing patient flow and shifting healthcare closer to home) so that less-efficient hospitals can emulate their peers.

In addition to the external factors which have been well established in the extant literature, our study has also made pioneering efforts to identify a number of internal factors which can be more easily targeted by hospital managers to improve efficiency. In particular,

we found that the management of internal resources can play a vital role in improving efficiency. The relationship identified in this study between asset utilization and efficiency suggests that acute foundation trusts need to maintain an optimal level of specific assets to provide services with an acceptable level of quality, and that this might be achieved by exploiting resources such as buildings and dwellings and applying information technology more effectively. Specifically, attention should be paid to estate management planning in which hospitals adequately assess the current state of assets used and carefully forecast the demands for services in the future. This action might pave the way for more detailed measures such as reconfiguration of hospital sites and hospital services to reduce unutilized spaces or additional measures to tackle maintenance backlogs and save on operating costs.

Measuring hospital efficiency is a complex and challenging task. This study provides evidence on the technical efficiency of English acute foundation trusts during a period of major restructuring and changes over recent years. In addition to the external factors which have been well examined in the literature, our study identified the determinants of efficiency, especially those related to internal factors which might provide more useful tools for hospital managers to directly target efficiency improvements. It thus serves to underline the importance of conducting second-stage regressions (hitherto widely neglected in the literature for UK hospitals) using a wide array of plausible patient, hospital, and asset variables to understand what is driving the observed efficiency.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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